

Switching from Cash to Cashless Payments during the COVID-19 Pandemic and Beyond*

Tomasz Piotr Wisniewski,^a Michal Polasik,^b
Radoslaw Kotkowski,^b and Andrea Moro^c

^aThe Open University

^bNicolaus Copernicus University in Toruń

^cLund University

Using a survey of 5,504 respondents from 22 European countries, we examine preferences regarding cash and cashless payments at the point of sale (POS) during the COVID-19 crisis. Consumers favor cashless transactions when they believe that handling cash presents a higher risk of infection. Moreover, the habits they develop during periods of restrictions and lockdowns appear to further diminish their appetite for transacting in cash. Not only do these factors affect current choice of payment method, but they also influence declared future intentions to move away from cash after the pandemic is over.

JEL Codes: E41, E42, I12, I18.

1. Introduction

The highly contagious coronavirus disease 2019 (COVID-19) was declared a pandemic on March 11 (World Health Organization 2020).

*This work was funded by the National Science Centre, Poland (Grant No. 2017/26/E/HS4/00858). We are grateful for the valuable comments and suggestions received during the “5th International Cash Conference: Cash in Times of Turmoil” organized by the Deutsche Bundesbank and at the “10th Economics of Payments” conference hosted by the Bank of Finland. Author contact: Tomasz Piotr Wisniewski: The Open University, Faculty of Business and Law, Walton Hall, Milton Keynes, MK7 6AA, United Kingdom; e-mail: tomasz.wisniewski@open.ac.uk. Michal Polasik: Nicolaus Copernicus University in Toruń, Faculty of Economic Sciences and Management, Gagarina 13a, 87-100 Torun, Poland; e-mail: michal.polasik@umk.pl. Radoslaw Kotkowski (corresponding author): Nicolaus Copernicus University in Toruń, Faculty of Economic Sciences and Management, Gagarina 13a, 87-100 Torun, Poland; e-mail: radoslaw.kotkowski@umk.pl. Andrea Moro: Lund University, CIRCLE - Centre for Innovation Research, Sölvegatan 16, Lund, S-22100, Sweden; e-mail: andrea.moro@circle.lu.se.

Up to the end of December 2023, it infected officially more than 774 million people and claimed almost 7 million lives (Mathieu et al. 2020). The mental, social, and economic lives of virtually everyone around the globe were affected by this health risk, profoundly changing people's habits and behaviors. In an attempt to limit the spread of the virus, governments enforced rules pertaining to social distancing and the use of face masks, advocated self-isolation, handwashing, and other types of hygienic measures. Partially due to government-imposed lockdowns, a significant reduction in people's mobility and consumption was observed, with a substitution from in-store to online shopping becoming particularly prominent (Bounie, Camara, and Galbraith 2023).

At the same time, an unprecedented outpouring of speculation about the possible link between handling physical money and COVID-19 infections has emerged (Auer, Cornelli, and Frost 2020). Research regarding this phenomenon indicated that a significant fraction of the population reduced their transactional use of cash in response to the pandemic. In its IMPACT study, the European Central Bank (2020) showed that about 40 percent of respondents in the euro area curtailed their use of cash and 38 percent of them declared that the main stimulus for their changed payment behavior was the possibility of being infected through touching banknotes. Surveys conducted by the Federal Reserve System (Kim, Kumar, and O'Brien 2020), Bank of Canada (Chen et al. 2020), and National Bank of Poland (Kotkowski, Dulnicz, and Maciejewski 2022) reached similar conclusions, noting further that some risk-averse merchants ceased to accept cash as a means of payment. Using the Dutch payment diary data, Jonker et al. (2022) shed more light on demographic and transaction-specific drivers that influence the change in payment habits due to COVID-19. Notably, the effect of the pandemic on the transactional utility of cash is manifest not only in declarations of individual respondents but also in more aggregate statistics. The studies focusing on data from retail systems, national payment schemes, or particular banks in Canada, Switzerland, Italy, and France revealed a rapid increase in the adoption of cashless payments, despite a decline in the level of general consumption (see Ardizzi, Nobili, and Rocco 2020; Bounie, Camara, and Galbraith 2023; Dahlhaus and Welte 2021; Kraenzlin, Meyer, and Nellen 2020).

In this paper, we further probe the utility of cash during the COVID-19 crisis. Using a unique data set, we can model respondents' inclination to switch from cash to cashless instruments. The richness of our data source permits us to disentangle two critical pandemic-related factors that drive underlying behaviors. Firstly, there is the direct impact of an individual's perception of viral transmission risk associated with touching banknotes and coins. Secondly, and equally importantly, this global health emergency has changed habits related to shopping, human interaction, mobility, health regimens, and ways of working. Entrenchment of these habits could have an indirect but lasting influence on payment method preferences. Our factor analysis indicated that those shifts in behavioral patterns could be categorized by whether they occurred in the physical sphere or in the cyberspace. By controlling for a wide range of respondents' and country-level characteristics, we extricated these direct and indirect influences in a logistic regression setting. We document that both fear of contagion and altered habits played a prominent role in the decision to abandon cash for transactional purposes during the COVID pandemic. Analogous results are obtained when modeling the respondents' intention to use cashless instruments more frequently after the pandemic is over. Notably, changes in habits related to physical contact exerted a more statistically and economically powerful impact on payment preferences of respondents than the altered behaviors in the online environment.

Several aspects distinguish our work from existing studies. The analysis of cash usage by the European Central Bank (2020) performed during the pandemic period reports only aggregated figures, without attempting to link COVID-19 responses to the selection of payment method at an individual level. Although Jonker et al. (2022) overcame this shortcoming by explicating changes in the payment behavior of Dutch consumers, our analysis is on a much larger scale—we examine 22 European countries rather than 1. What is more, to the best of our knowledge, this is the first study empirically linking the magnitude of fear of viral contagion with the choice of payment instrument. Similarly, the fact that changes in other habits could have a domino-like effect on peoples' payment choices has hitherto not been considered in the literature. To add further depth to our inquiry, we not only consider historical preferences towards

cashless payments, but also interrogate individuals' declarations about their future payment intentions after the COVID-19 pandemic is over. Our empirical model controls for a wide range of factors, including perceptions of different payment instruments, experience of using them, stances on privacy, general technical literacy, a variety of sociodemographic factors, and country-level variables such as the number of COVID-related deaths and size of the shadow economy.

The remainder of the paper is organized as follows. Section 2 presents a literature review, which embodies two important themes. It starts by reviewing the evidence on SARS-CoV-2 survival on banknotes and coins, moving subsequently to a consideration of consumer payment behavior. Section 3 outlines our methodological approach, while Section 4 provides a description of the data set, definitions of variables, and a set of summary statistics. Our main empirical results and their interpretation are included in Section 5, and this is followed by a battery of robustness checks in Section 6. Section 7 presents reflections on the practical implications of our findings. The paper ends with concluding remarks.

2. Literature Review

2.1 Methods of Payments and Infectious Disease Transmission

Studies examining the spread of pathogens through the use of cash date back to the 1970s (see, for instance, Abrams 1972). In absence of disinfection, various types of microbes could adhere to the surface of currency, leading to the transmission of communicable diseases. A study by Vriesekoop et al. (2016) exploring bacterial survival concluded that microbial persistence is greater on paper banknotes than on polymer bills and coins. According to the estimates of Pope et al. (2002), about 94 percent of \$1 bills are contaminated with pathogenic or potentially pathogenic bacteria. This statistic reaches 100 percent for currency notes in Ghana (Tagoe et al. 2009). Bills could also potentially harbor fungi and yeast (Basavarajappa, Rao, and Suresh 2005), parasites (Uneke and Ogbu 2007), and viruses (Maritz et al. 2017). The literature review conducted by Angelakis et al. (2014) concludes that banknotes

retrieved from hospitals may carry antibiotic-resistant MRSA, while those from food outlets may be tainted with salmonella and *E. coli*.

While the existence of the monetary microbiome is well documented in the medical literature, one may wonder to what extent this message reverberated through broader society prior to the COVID-19 crisis. The reaction to the study of Gedik, Voss, and Voss (2013) epitomizes the attitudes of the bygone era. Their insightful analysis examined bacterial survival on banknotes from different countries. For their work, the authors received a satirical Ig Nobel Prize for economics in 2019. One year later, the escalating death toll from coronavirus caused a sea change in general attitudes towards this problem.

Discovery of durability of SARS-CoV-2 on surfaces (Chin et al. 2020; van Doremalen et al. 2020) posed a question as to whether the virus could be transmitted via cash. Having put a droplet of the virus on a banknote, Chin et al. (2020) observed that the note remained infectious for a period of four days. Harbourt et al. (2020) investigated the persistence of SARS-CoV-2 on U.S. banknotes produced from a blend of linen and cotton. At a temperature of 4°C, the virus was detectable for 96 hours on \$1 bills and for 72 hours on \$20 notes. Surface stability however reduced with ambient temperature, with the virus being viable for eight hours at 22°C and for four hours at 37°C. A study commissioned by the Bank of England (Caswell et al. 2020) found that the virus maintained its stability on banknotes for one hour, with its presence being dramatically reduced to about 5 percent of its initial level over the subsequent five hours. Those are very low estimates compared to those of Riddell et al. (2020), who claim that the coronavirus causing COVID-19 is still detectable on polymer and paper notes 28 days following inoculation. With regard to coins, the time to complete virus decay may depend on the metal used to mint the coin. For instance, this duration appears to be 8 hours for copper and 48 hours for stainless steel (van Doremalen et al. 2020). At the time of writing, there are still many questions as to whether cash is indeed a fomite and what exactly is the severity of the risks involved. The general public was bombarded with mixed messages in this regard. For instance, the World Health Organization has recommended that people wash their hands after coming in contact

with notes and coins (Pal and Bhadada 2020). However, a recent study commissioned by the European Central Bank (ECB) showed that the risk of contracting the disease from contact with cash is very low and that cash is reasonably safe to use (Tamele et al. 2021).

The question arises as to whether the dangers posed by cash can be circumvented by switching to cashless payments. After all, SARS-CoV-2 can remain stable on plastic surfaces for seven days (Chin et al. 2020), which in itself could endanger users of payment card terminals and PIN (personal identification number) pads. However, limits on contactless payments were increased in many countries during the pandemic (Mastercard 2020), obviating the need to input a PIN code for most transactions at the point of sale. The vast majority of transactions conducted online or via mobile banking also do not require contact with potentially contaminated surfaces. Consequently, one may argue that changing one's payment habits may reduce the risk of infection.

The stance of money issuers vis-à-vis the problem of jeopardized public health proved to be somewhat confusing. Central banks differed markedly in terms of their response to information about the potential threat posed by cash. Some central banks (such as the ECB and those of the United Kingdom, Germany, Austria, Sweden, and South Africa) either stressed that the risk of SARS-CoV-2 transmission through cash is minimal compared to other frequently touched objects or refused to acknowledge the possibility of contagion altogether. But a few other nations took different approaches. For instance, central banks in the United States, China, South Korea, Kuwait, Hungary, and Poland started to quarantine and disinfect cash (Auer, Cornelli, and Frost 2020; King and Shen 2020). A regional branch of the People's Bank of China proceeded to destroy banknotes that had circulated in hospitals, wet markets, and on buses (Yeung 2020). The central banks of Georgia and India started to promote cashless payments, while, at the other end of the spectrum, monetary authorities in Canada, Portugal, and Poland appealed to retailers who stopped accepting cash to discontinue such practices. Their pleas were motivated by concerns over those who are financially excluded.

2.2 *Consumer Payment Behavior*

Consumer payment behavior has been a burgeoning field of research since the 1980s, starting with the seminal work of Boeschoten and Fase (1989). Nowadays, country-specific inquiries into this topic are primarily carried out by central banks. The U.S. Federal Reserve has been conducting an annual Survey of Consumer Payment Choice since 2008 (Foster, Greene, and Stavins 2020) and a Diary of Consumer Payment Choice since 2015 (Greene and Stavins 2020). In a similar vein, studies regarding Dutch payment behavior have been undertaken by De Nederlandsche Bank (DNB) since 2010 (see DNB 2020). A number of other countries, including Australia, Canada, Denmark, Sweden, Germany, Poland, and Norway, also endeavor to run similar surveys at regular intervals. Going beyond national level, the ECB performed its pan-euro-area study in 2016 (see Esselink and Hernández 2017) and 2019 (ECB 2020). Taken together, the evidence gathered reveals a pattern of steady decline in the share of retail transactions conducted using cash. In the United States this share fell from about 30 percent in 2009 to 21.5 percent in 2019 (Foster, Greene, and Stavins 2020). This downward-sloping trend is mirrored in the United Kingdom with a decline from about 80 percent in 1990 to 23 percent in 2019 (Caswell et al. 2020) and in the euro area, where the proportion of cash POS and P2P (peer-to-peer) payments decreased from 79 percent to 73 percent between 2016 and 2019 (ECB 2020).

Personal payment choice is an outcome of myriad variables, both intrinsic and extrinsic to a given individual. Internal aspects embrace perceptions of different payment instrument characteristics such as perceived speed of payment, security, ease of use, and budget control (Koulayev et al. 2016; Schuh and Stavins 2016), or stances on issues like privacy and trust (Png and Tan 2020). External influences could incorporate, for instance, socioeconomic and sociopsychological factors (Stavins 2001; van der Cruijssen and van der Horst 2019). It is worth noting that the characteristics of transactions could be also important in terms of influencing the outcome. Such characteristics encompass the transaction amount (Arango-Arango et al. 2018; Wang 2016), the possibility of paying in the way one desires (Bagnall et al. 2016; Bounie, François, and Van Hove 2017), steering mechanisms used by merchants (Arango, Hyunh, and Sabetti 2015; Stavins

and Shy 2015), rewards offered by issuers of cashless payments (Bolt, Jonker, and van Renselaar 2010; Simon, Smith, and West 2010), or costs associated with the transaction (Arango-Arango et al. 2018).

Prior to the COVID-19 outbreak, there was little research investigating the link between spread of contagious disease and change in people's payment behavior. Closest to this subject is the work by Galbraith and Tkacz (2013), who used payment systems data to examine the economic impact of extreme events, like the 9/11 terrorist attacks and the SARS epidemic of March–June 2003. However, at the time, the SARS epidemic did not alter behavior significantly enough to generate detectable effects. Following the escalation of COVID-19, more research on this topic started to emerge. Apart from our study, other papers that used individual-level data include the aforementioned work of Jonker et al. (2022) and that of Saroy et al. (2022) who documented a pandemic-induced shift towards cashless payments in India. The authors argued that awareness of digital payment methods, access to different instruments, and relief welfare transfers affected the shift. Another study by Cevik (2020) reported that the spread of contagious diseases like Ebola, SARS, malaria, or yellow fever decreased the demand for physical money in the affected areas and noted that this observation may have ramifications for the current situation.

Ours is a paper that focuses specifically on how the context of the COVID-19 pandemic affected intentions to use cash. In our exploration, we distinguish two important mechanisms through which such intentions could be affected. First, individuals may exhibit varying degrees of subjective fear attributable to dealing with currency that could potentially be virally contaminated. Such fears would be a direct stimulus steering consumers towards cashless transactions, insofar as cashless transactions are perceived as a lower contagion risk. Second, there could be an indirect effect arising from the fact that the pandemic has profoundly altered our ways of life. Bound by government restrictions and by the commonsensical avoidance of jeopardy, individuals showed a stronger preference for online shopping (Bounie, Camara, and Galbraith 2023; Watanabe and Omori 2020), reduced their mobility and consumption (Bounie, Camara, and Galbraith 2023; Carvalho et al. 2021; Mínguez, Urtasun, and de Mirasierra 2020), modified their working practices (Bick, Blandin, and Mertens 2023; Brynjolfsson et al. 2020), and moved their social

interactions into cyberspace (Nabity-Grover, Cheung, and Thatcher 2020). Such lifestyle transformations could have serious ramifications for personal preferences over payment methods.

A question arises as to whether these lifestyle changes have become habitual and therefore enduring. We need to bear in mind that focal attention and consciousness of choice feature prominently when an action is performed for the first time. The more an activity is repeated in a stable context, the more automatic the cognitive processes become, thereby permitting speedy action (Carden and Wood 2018; Shiffrin and Schneider 1977). Lally et al. (2010) examined changes in daily routines in order to gauge how long it would take an individual to develop a new habit. In their research, the participants' median time to reach a "plateau of automaticity" was 66 days. The duration of the pandemic has exceeded this estimate by a substantial margin, allowing sufficient time for habit formation. Arguably, the context could be also viewed as stable in the sense that the possibility of infection was ubiquitous and ever-present. However, there is a fair amount of uncertainty as to how people would behave if the context were to change. For instance, the epidemic could be eradicated through a program of mass vaccination. In response to this, some individuals may remain entrenched in the habits they acquired, while others may devote more attention to accommodating the altered landscape in their decisionmaking. Any persistence of COVID-induced habits could affect general attitudes towards using cash in the long run. Our questionnaire deliberately asks respondents which of their behavioral changes are likely to endure one year after the end of the COVID-19 pandemic.

3. Methodology

Two dependent dummy variables are considered in our modeling. They record whether respondents started to use more cashless payments due to the COVID-19 pandemic (*Cashless Switch*) and whether they declare an intention to use cashless payments more often after the pandemic is over (*Cashless Intention*). Since our data set is cross-sectional rather than longitudinal in nature, we are unable to verify whether the declared intentions materialize as an actual behavior in the future. However, extant empirical evidence indicates that, when it comes to adopting technologies,

there is a high correlation between intentions and actual subsequent usage (see, for instance, Davis 1989). Perhaps more importantly, the behavioral intention is considered an antecedent and a stimulus for technology adoption in the most prominent theoretical models, such as the theory of reasoned action (Ajzen and Fishbein 1980; Fishbein and Ajzen 1975) or the technology acceptance model (Davis 1989).

Since our dependent variables measuring whether a respondent switched or intends to switch to cashless payments are binary in nature, our analysis relies on traditional logit regressions (Hosmer, Lemeshow, and Sturdivant 2013). Consequently, we estimate the probability of the act or intention to switch by employing the following empirical model:

$$P(Y_{jk}^i = 1 | H_{jk}, E_k, C_{jk}) = \frac{1}{1 + e^{-(\alpha + \beta(H_{jk}) + \varphi(E_k) + \gamma(C_{jk}))}} \quad (1)$$

Two variants ($i \in \{1, 2\}$) of the dependent variable Y^i are used in the main analysis and the robustness check section, representing either *Cashless Switch* or *Cashless Intention*. Depending on the value of i , the outcome $Y^i = 1$ indicates that the person either switched to cashless payments or wishes to do so in the future; H_{jk} is the vector that measures the characteristics, perceptions, and confidence in using technology of person j living in country k ; E_k is a vector of specific characteristics of country k ; while C_{jk} is our core vector of COVID-19-induced fears and changes in the behavior of person j living in country k .

Our sampling uses stratification by age, gender, and size of locality, and the survey spans 22 European countries. However, the sample size in each of the nations is not necessarily proportional to its population of Internet users. To remedy this issue methodologically, we proceed to calculate the actual proportions of Internet users for each country and, in our estimation, we weight each observation by the inverse of its probability of being sampled. In other words, the higher the weighting, the higher the observation's contribution to the residual sum of squares. Such an approach is commonly used in the literature (see, for instance, Moro et al. 2020). We note in passing that unweighted estimation results lead to identical conclusions regarding the processes being modeled.

Since the standard variance-covariance matrix is no longer appropriate, we use a sandwich (White 1980) estimator to compute it.

Robust estimation of standard errors is relied upon to deal with heteroskedasticity issues. When fitting the regressions, we take necessary precautions to avoid multicollinearity problems. This is accomplished by performing factor analysis that aggregates cognate questionnaire items into a construct. Most notably, we consider two factors representing the change in habits related to the COVID-19 epidemic, which have the potential to explain the curbed appetite for cash and transcend purely fear-based rationalization.

4. Data

Collection of the data used in this study was supported by a research grant awarded by the Polish National Science Centre and was implemented by a research agency, Interactive Research Center. The source data were obtained from consumers through a survey based on computer-assisted web interviews (CAWI), which utilized an interactive Internet questionnaire. Internet users were invited to register their interest in participating through e-mail and advertising campaigns. Those who volunteered collected points that were redeemable for prizes. Survey respondents were then selected through stratified sampling from the pool of registrants. Such a data collection approach permitted us to obtain a large sample in a relatively cost-effective manner. The interactive nature of the survey afforded us the opportunity to incorporate additional clarifications and definitions of the technical terms that could be accessed by respondents without the need to exit the webpage. CAWI also allowed participants to pause and save the answers that have already been submitted, facilitating thereby the process of consulting external information sources whenever needed.

The data collection exercise was preceded by a pilot study involving 230 respondents from 22 countries. The overriding aim of this undertaking was to verify whether respondents understand and interpret the questionnaire items correctly. Minor irregularities that were identified in the questionnaire were subsequently rectified and there was no need to conduct a second pilot study. The final sample, collected during the period spanning July to August 2020, includes 5,504 respondents from 22 European countries (Austria, Belgium, Bulgaria, Czech Republic, Denmark, Finland,

France, Germany, Greece, Hungary, Ireland, Italy, Lithuania, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Spain, Sweden, United Kingdom). According to Eurostat (2020), the number of Internet users in those countries accounted for 96 percent of all Internet users in the European Union in 2019.

Our survey was conducted online as, due to the pandemic, conducting face-to-face interviews would not have been possible. Since only individuals with Internet access could participate, this raises a question of whether our sample is sufficiently representative of the entire population in terms of the problem studied. To assess the gravity of this problem, we collect Eurostat data on the prevalence of Internet use in the countries of interest. The country-level statistics (presented in Appendix A) were subsequently weighted by population (taken from the World Development Indicators, WDI, database) to arrive at a sample average. The 2020 statistics indicate that proportion of individuals who used Internet in the last 12 months was 90.5 percent, while the proportion of people who have ever used it stood at 92.0 percent. Fortunately, the issue of potential non-representativeness may be even less significant than these statistics would indicate for reasons elucidated in Grewenig et al. (2023). They show that although it may be possible that onliners and offliners differ in their answering behavior, once both groups are interviewed in the face-to-face mode and individuals' background/demographic characteristics are controlled for, the statistical differences between the groups evaporate. We would like to note that our regressions account for demographic factors, which is likely to reduce the size of any possible bias arising from sampling to a tolerable level.

The data collection process employed stratified random sampling, with age, gender, and size of the respondent's locality acting as stratification factors. The stratification factors of gender, age, and size of locality are also used as controls in our regressions. Another control variable employed is the attitude towards privacy, which was quantified through a questionnaire item stating: "I prefer payments for shopping to be anonymous, so that no one can see what I bought and when." The possession of a card, mobile, or wearable that could be used at the point of sale is captured by the dummy variable *Cards & Mobile*. Individuals who are lacking such items face higher costs of switching to cashless technologies, in that they may be forced to open a bank account or acquire the requisite device. We also consider eight

other variables that measure the respondents' perceptions, experience, technological literacy, and habits and that are built up as constructs using principal component factor analysis (Hair et al. 2013). Each of these constructs includes many highly correlated items that cannot be modeled separately due to multicollinearity problems.

The first set of factors examines the assessment of alternative cashless payment methods, namely NFC (or near-field communication) contactless payments like Google Pay, Apple Pay, or payments with wearables (smartwatches, smartbands), and QR (quick response) code payments. Each payment method is assessed across several dimensions using a five-point Likert scale, and one factor for each of the dimensions is subsequently extracted. These factors are labeled as *Convenience of Cashless Payments*, *Safety of Cashless Payments*, *Access to Cashless Payments Technologies*, *Ease of Use of Cashless Technologies*, and *Control over Finance with Cashless Payments*. Familiarity with technologies was encapsulated in three additional factors. The first one, called *Literacy in Using Mobile Apps*, is based on five items assessing how confident the surveyed person is in using mobile apps for transport (e.g., Uber, Bolt, Freenow), food delivery, buying tickets on public transport, paying parking fees, and tracking fitness activity. Moreover, we measure experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE (host card emulation, or mobile contactless in a card-issuer app). Principal component analysis suggests extraction of two factors (eigenvalues of 2.91 and 1.18) that are subsequently rotated using varimax rotation. The items that load clearly in one factor measure *Experience in Using Computer Payments*, while the second factor captures *Experience in Using Mobile Payments*.

Furthermore, our questionnaire comprised a series of items pertaining to habit formation during the pandemic. These items were prefaced by a request to provide an assessment of how the respondent's life will change one year after the COVID-19 pandemic is over, as compared to the time before it started. Responses to these questions were recorded on a five-point Likert scale. The first variable measured the impact of the pest on working habits ("I will work more remotely"), while the second one was designed to capture a possible increase in online activity as a substitute for physical contact

(“I will meet people online more frequently”). We also endeavored to explore a shift in traveling patterns (“I will travel less in my country” and “I will travel less abroad”), as well as dining habits (“I will eat more frequently at home”). Finally, we evaluated whether COVID-19 affected personal perception of health (“I will be more focused on my health”) and shopping preferences (“I will buy more online”). Two factors with eigenvalues of 2.97 and 1.01 are extracted from these predictions of future habits. The items that load clearly on the first factor capture *Change in Habits Related to Physical Contact*, while the second one clearly gauges *Change in Online Habits*.

All of the eight above-mentioned factors created for the purpose of this study underwent a rigorous process of verification with respect to internal consistency and sampling adequacy. Statistics related to this verification are reported in Table 1. By default, each of the constructs has an eigenvalue above unity. Reassuringly, the Cronbach’s alphas are consistently above the recommended threshold of 0.60. The Keiser-Meyer-Olkin test does not detect any sampling inadequacy requiring remedial action, and the proportion of variance explained by the factors appears to be satisfactory.

Moving away from factors, we explore another measure that is critical to our investigation. It intends to capture individual fear related to the possibility of contracting the disease through contact with cash. However, one needs to bear in mind that measurement must be done in relative terms. Respondents will be deterred from using cash for transitional purposes only if they perceive its infection risk to be higher than that for cashless instruments. For this reason, there was a need to include two items in the questionnaire which read “I am afraid of contracting COVID-19 due to the usage of cash in physical stores” and “I am afraid of contracting COVID-19 as a result of operations with cashless payments in physical stores.” By taking the difference between the responses to these two questions, we construct a variable called *Net Fear of Cash*. Since the original items were measured on a five-point scale, the resultant net fear variable ranges from -4 to $+4$.

Finally, we utilize three variables that are measured at the country level. We include the cumulative number of COVID-19 deaths (in thousands) that occurred prior to July 2020 in order to consider the general impact that the pandemic had in a given country. Furthermore, the estimated size of the shadow economy in 2016 (as

Table 1. Characteristics of Factors Used in the Study

Factor	Eigenvalue	Cronbach's Alpha	Proportion of Variance Explained	Kaiser-Meyer-Olkin Measure
<i>Convenience of Cashless Payments</i>	3.6510	0.8665	0.7302	0.8751
<i>Safety of Cashless Payments</i>	3.9730	0.9346	0.7945	0.8897
<i>Access to Cashless Payments Technologies</i>	3.7631	0.9161	0.7526	0.8735
<i>Ease of Use of Cashless Technologies</i>	3.8451	0.9236	0.7690	0.8774
<i>Control over Finance with Cashless Payments</i>	4.1703	0.9495	0.8341	0.8968
<i>Literacy in Using Mobile Apps</i>	2.3729	0.7208	0.4746	0.7818
<i>Experience in Using Computer Payments</i>	2.1871	0.6027	0.3701	0.8265
<i>Experience in Using Mobile Payments</i>	1.9133			
<i>Change in Habits Related to Physical Contact</i>	2.9795	0.7722	0.5710	0.8265
<i>Change in Online Habits</i>	1.0172			

a percentage of GDP) was considered as an explanatory variable for cash preferences arising from tax evasion and illegal activities. These estimates were sourced from Kelmanson et al. (2019). Lastly, we create a variable measuring the number of EFT-POS terminals per 1,000 inhabitants in 2020 based on the data published by Bank for International Settlements (2022), ECB (2022), and Norges Bank (2020).¹

Table 2 provides definitions of all the variables used in the study, while Table 3 reports the corresponding summary statistics. Evaluation of these statistics paints a picture of the individuals involved in our survey. An average respondent resided in a city with less than 100,000 inhabitants and was 47 years of age. The latter figure was influenced by the fact that people under the age of 18 were not invited to participate. Women constituted 52 percent of the sample, which is representative of the broader population in the countries of interest. On average, those who were surveyed showed a slight preference towards payment anonymity but tended to pay primarily with cards and mobiles at the point of sale. When analyzing Table 3, one needs to bear in mind that all the constructs created through factor analysis have a mean of zero and a standard deviation of one.

Importantly, 41 percent of people declared that they use cashless payments more often during the COVID-19 crisis, while 47 percent stated that they will use cashless payments more frequently after the pandemic is over. An average respondent believed that the risk of contracting the coronavirus is slightly higher for cash than the cashless alternatives. Appendix B provides more detailed data in this regard by presenting a breakdown of the key variables by country. Judging from these statistics, respondents who were most keen to switch from cash to digital payments during the pandemic resided in the United Kingdom, Belgium, Ireland, and Portugal. In those countries, people were also more likely to declare their intention to further increase the frequency of cashless payments after the pandemic has been eradicated. Such behavior could be explained by the above-average fear of virus transmission through cash as compared

¹Since the 2020 data had two missing observations (Bulgaria and Norway), we resorted to using 2019 figures for these two countries. In our judgment, this is a sensible solution since the state of the payment infrastructure does not change rapidly on a year-to-year basis.

Table 2. Definitions of Variables

Variable	Definition
<i>Cashless Switch</i>	A binary variable taking the value of one for the response “Yes, I pay more often cashless (by card, smartphone, smartwatch)” to the questionnaire item “Has the coronavirus pandemic (COVID-19) affected how you pay in physical stores?”. The responses “Yes, I pay more cash,” “Not affected (I pay the same way as I did before pandemic,” “I do not know,” and “I did not make any purchases during pandemic” are coded as zero.
<i>Cashless Intention</i>	Dummy variable measuring respondent’s agreement with the statement “After the pandemic, I will use cashless payments more often” (1 = yes, 0 = no)
<i>Gender</i>	Dummy variable capturing respondent’s gender (1 if female, 0 otherwise)
<i>Location Size</i>	Response to a question regarding the size of the location (including suburbs) where the respondent lives. Responses are coded on a six-point scale:
	1 – Rural area
	2 – City with less than 50,000 inhabitants
	3 – City between 50,000 and 100,000 inhabitants
	4 – City between 100,000 and 500,000 inhabitants
	5 – City between 500,000 and 1,000,000 inhabitants
	6 – City over 1,000,000 inhabitants
<i>Age</i>	Age of the respondent
<i>Cards & Mobile</i>	A dummy variable measuring the possession of any card, mobile, or wearable applicable at the point of sale (1 = yes, 0 = no)
<i>Anonymity</i>	Degree of agreement with a statement “I prefer payments for shopping to be anonymous, so that no one can see what I bought and when” measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree)
<i>Convenience of Cashless Payments</i>	A factor aggregating assessments of convenience of five different cashless payment technologies (contactless (NFC) payments, Google Pay, Apple Pay, QR code payments, contactless payments with wearables)
<i>Safety of Cashless Payments</i>	A factor combining perceptions of safety of five different cashless payment technologies
<i>Access to Cashless Payments</i>	A factor aggregating assessments of how widespread five different cashless payment instruments are
<i>Ease of Use of Cashless Technologies</i>	A factor extracted from evaluations of how easy to use five cashless payment technologies are

(continued)

Table 2. (Continued)

Variable	Definition
<i>Control over Finance with Cashless Payments</i>	A factor constructed from an assessment of how much control over personal finance is afforded by five different cashless payment technologies
<i>Literacy in Using Mobile Apps</i>	A factor aggregating five items assessing how confident the surveyed person is in using mobile apps for transport (e.g., Uber, Bolt, Freenow), food delivery, buying tickets on public transport, paying parking fees, and tracking fitness activity
<i>Experience in Using Computer Payments</i>	First factor extracted from the items measuring respondent's experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE. The items that load clearly relate to computer-based payments.
<i>Experience in Using Mobile Payments</i>	Second factor extracted from the items measuring respondents' experience in using payment technologies such as Apple Pay, Google Pay, Amazon Pay, Alipay, MoneyGram, Samsung Pay, WeChat Pay, Western Union, Revolut, cryptocurrencies, and HCE. The items that load clearly relate to mobile-based payment technologies.
<i>Change in Habits Related to Physical Contact</i>	First factor extracted from items "I will work more remotely," "I will meet people online more frequently," "I will travel less in my country," "I will travel less abroad," "I will eat more frequently at home," and "I will be more focused on my health" after the COVID-19 crisis is over. The items that load heavily are related to physical contact.
<i>Change in Online Habits</i>	Second factor extracted from items "I will work more remotely," "I will meet people online more frequently," "I will travel less in my country," "I will travel less abroad," "I will eat more frequently at home," and "I will be more focused on my health" after the COVID-19 crisis is over. The items that load heavily are related to online habits.
<i>Net Fear of Cash</i>	A variable constructed by taking the difference in responses to two questionnaire items: "I am afraid of contracting COVID-19 due to the usage of cash in physical stores" and "I am afraid of contracting COVID-19 as a result of operations with cashless payments in physical stores."
<i>COVID Deaths</i>	Total number of COVID-19 deaths (in thousands) for the country in which the respondent resides
<i>Shadow Economy Number of EFT-POS Terminals per Thousand People</i>	Size of the shadow economy as a percentage of GDP in the respondent's country of residence Number of terminals provided by resident payment service providers per thousand inhabitants

Table 3. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	25th Percentile	Median	75th Percentile	Maximum
<i>Cashless Switch</i>	0.47	0.50	0.00	0.00	0.00	1.00	1.00
<i>Cashless Intention</i>	0.41	0.49	0.00	0.00	0.00	1.00	1.00
<i>Gender</i>	0.52	0.50	0.00	0.00	1.00	1.00	1.00
<i>Location Size</i>	2.77	1.57	1.00	1.00	2.00	4.00	6.00
<i>Age</i>	47.04	16.31	18.00	33.00	47.00	62.00	100.00
<i>Cards & Mobile Anonymity</i>	0.90	0.30	0.00	1.00	1.00	1.00	1.00
<i>Convenience of Cashless Payments</i>	3.28	1.12	1.00	3.00	3.00	4.00	5.00
<i>Safety of Cashless Payments</i>	0.00	1.00	-2.05	-0.45	-0.06	0.67	1.94
<i>Access to Cashless Payments Technologies</i>	0.00	1.00	-2.29	-0.21	-0.02	0.80	1.88
<i>Ease of Use of Cashless Technologies</i>	0.00	1.00	-2.37	-0.36	-0.14	0.56	2.09
<i>Control over Finance with Cashless Payments</i>	0.00	1.00	-2.59	-0.45	-0.07	0.62	1.70
<i>Literacy in Using Mobile Apps</i>	0.00	1.00	-2.36	-0.29	-0.29	0.74	1.78
<i>Experience in Using Computer Payments</i>	0.00	1.00	-0.88	-0.88	-0.31	0.52	2.42
<i>Experience in Using Mobile Payments</i>	0.00	1.00	-1.36	-0.20	-0.20	-0.20	9.66
<i>Change in Habits Related to Physical Contact</i>	0.00	1.00	-2.97	-0.52	-0.52	0.43	5.90
<i>Change in Online Habits</i>	0.00	1.00	-2.93	-0.53	-0.02	0.61	2.56
<i>Net Fear of Cash</i>	0.00	1.00	-3.64	-0.59	0.16	0.68	3.19
<i>COVID Deaths</i>	0.24	1.01	-4.00	0.00	0.00	0.00	4.00
<i>Shadow Economy</i>	8.49	5.18	2.47	4.99	6.25	11.48	20.98
<i>Number of EFT-POS Terminals per Thousand People</i>	21.98	7.18	9.60	16.70	20.30	27.80	37.80
	30.35	13.97	13.18	23.01	26.79	32.99	71.11

Note: Definitions of the variables can be found in Table 1. The number of observations for each of the variables listed above is 5,504.

to cashless alternatives as well as significant shifts in habits spanning both the physical and virtual realms.

Another point of interest is the joint distribution of the two dependent variables in our study. The data reported in Appendix C reveals that the values of *Cashless Switch* and *Cashless Intention* coincide for 70.35 percent of respondents. This is unsurprising, as these variables are expected to have common covariates. When we partition our sample based on the values of the two dependent variables, we discover that significant differences in the average value of *Net Fear of Cash* emerge across different subgroups. This preliminary result indicates that the fear of infection through handling physical currency is determining payment behavior.

5. Empirical Results

Table 4 presents the results of weighted logit regressions estimating the likelihood of an immediate increase in the frequency of cashless payments in response to the COVID-19 pandemic. The first specification focuses on the fear of contagion via cash, while the second one considers the impact of changing habits. Regression (3) subsumes both these determinants as well as a full set of controls, making it the most comprehensive model amongst the considered alternatives. With respect to the key explanatory variables, our empirical findings cohere with a priori predictions. *Net Fear of Cash* is positively signed and exhibits a strong statistical significance. Clearly, individuals who believe that handling cash poses a relatively serious health hazard tend to enthusiastically embrace cashless instruments. The *t*-statistics associated with the variable *Change in Habits Related to Physical Contact* exceed the value of 10, making it another strong predictor of payment behavior. In other words, respondents who declared an intention to alter their routines in the physical world were *ceteris paribus* more likely to use cashless payment methods at the point of sale. *Change in Online Habits* appears to be a further important explanatory factor, albeit the magnitude of its coefficient and its explanatory power pales in comparison to the *Change in Habits Related to Physical Contact*. One may therefore argue that, when it comes to choices of payment technologies, habits in the physical sphere are of greater consequence than those in the virtual realm.

Table 4. Modeling the Switch to Cashless Payments during the Pandemic

	(1)	(2)	(3)
<i>Gender</i>	0.1764** (0.0762)	0.1528** (0.0774)	0.1597** (0.0778)
<i>Location Size</i>	0.0265 (0.0249)	0.0150 (0.0253)	0.0189 (0.0255)
<i>Age</i>	0.0047* (0.0025)	0.0066** (0.0026)	0.0063** (0.0026)
<i>Cards & Mobile</i>	0.6695*** (0.1323)	0.7438*** (0.1334)	0.7286*** (0.1336)
<i>Anonymity</i>	-0.0560* (0.0335)	-0.1230*** (0.0346)	-0.1082*** (0.0349)
<i>Convenience of Cashless Payments</i>	0.0079 (0.0534)	-0.0261 (0.0559)	-0.0210 (0.0560)
<i>Safety of Cashless Payments</i>	0.1188** (0.0594)	0.1245** (0.0598)	0.1140* (0.0604)
<i>Access to Cashless Payments Technologies</i>	0.0247 (0.0535)	-0.0431 (0.0547)	-0.0360 (0.0552)
<i>Ease of Use of Cashless Technologies</i>	0.1515** (0.0601)	0.1707*** (0.0616)	0.1600*** (0.0617)
<i>Control over Finance with Cashless Payments</i>	0.0107 (0.0530)	-0.0210 (0.0536)	-0.0244 (0.0544)
<i>Literacy in Using Mobile Apps</i>	0.3763*** (0.0467)	0.3655*** (0.0469)	0.3630*** (0.0472)
<i>Experience in Using Computer Payments</i>	0.0631* (0.0361)	0.0166 (0.0369)	0.0219 (0.0373)
<i>Experience in Using Mobile Payments</i>	0.0420 (0.0442)	0.0172 (0.0460)	0.0195 (0.0457)
<i>COVID Deaths</i>	0.0245*** (0.0072)	0.0174** (0.0074)	0.0183** (0.0075)
<i>Shadow Economy</i>	-0.0132** (0.0057)	-0.0192*** (0.0058)	-0.0201*** (0.0058)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0031 (0.0025)	0.0002 (0.0025)	0.0011 (0.0026)
<i>Net Fear of Cash</i>	0.2812*** (0.0389)		0.2431*** (0.0399)
<i>Change in Habits Related to Physical Contact</i>		0.4748*** (0.0421)	0.4526*** (0.0422)
<i>Change in Online Habits</i>		0.0981** (0.0392)	0.0984** (0.0394)
Constant	-1.0736*** (0.2822)	-0.6432** (0.2883)	-0.7457** (0.2907)
Observations	5,504	5,504	5,504
chi2	343.0	391.3	429.5
p-value	0	0	0
McFadden's Pseudo R-squared	0.0885	0.108	0.117

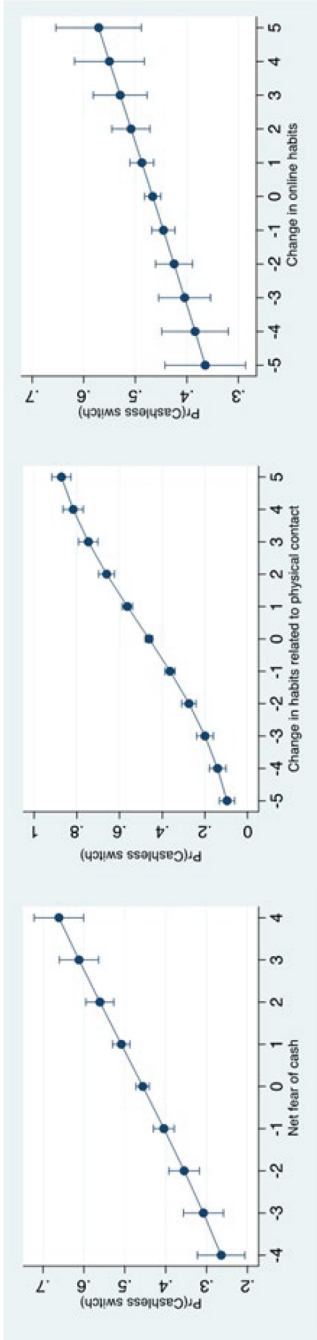
Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

While the statistical significance of fear and habits is unequivocal, the question arises as to the economic significance of our results. To probe this issue, we plot predictive functions in panel A of Figure 1. More specifically, these plots show the expected probability of *Cashless Switch* = 1 when one key independent variable is varied, and the remaining regressors are kept constant at the sample average value. When interpreting the values on the horizontal axis, one needs to remember that *Net Fear of Cash* was derived from differencing two five-point Likert scales, while a unitary move across the x-axis for the habit variables denotes a change equivalent to one standard deviation. Clearly, probabilities are increasing monotonically with all three of the variables considered in panel A, with the increase being remarkably steep for *Net Fear of Cash* and *Change in Habits Related to Physical Contact*. Judging from the plots, these two factors were decisive for many respondents in their decision to abandon cash payments at POS during the COVID-19 crisis.

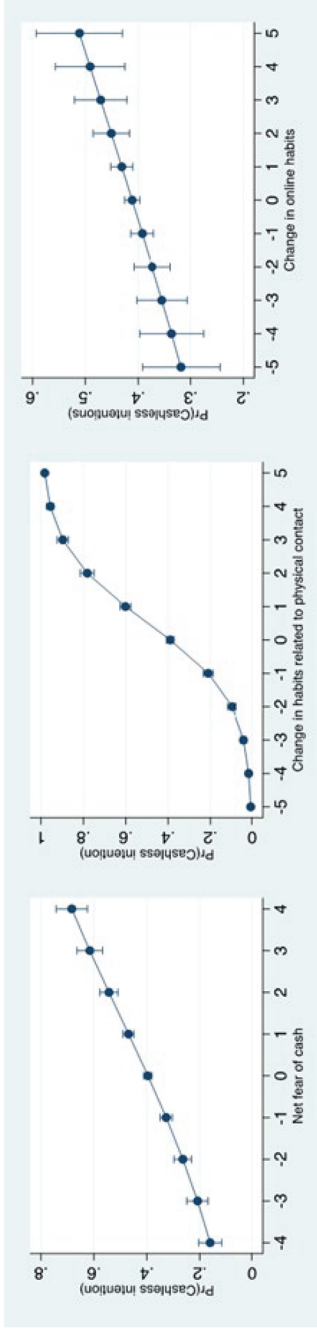
The influence of statistically significant control variables warrants further discussion. Females and those who are literate in using mobile apps showed greater proclivity to embrace cashless technologies. Unsurprisingly, those without access to cashless instruments remained dependent on banknotes and coins during the COVID crisis. Since older individuals face higher SARS-CoV-2 fatality rates (O'Driscoll et al. 2021), their health risk arising from engagement in cash-based transactions is graver. Cognizant of this reality, older people relinquished payments with physical currency more readily. Apprehension over anonymity issues and the influence of shadow economy thwarted individuals' transition towards cashless transacting. Respondents with no concerns over safety of digital payment technologies were more likely to use them frequently, which mirrors the argument of Ostlund (1974) that the perceived risk of an innovation hinders its diffusion. Furthermore, in line with the theoretical predictions of the technology acceptance model of Davis (1989), perceived ease of use of cashless instruments correlated positively with their adoption. Lastly, the number of COVID-related deaths in the respondent's country of residence was a factor contributing to the abandonment of cash. The number of deaths captures general concern over the pandemic, which goes beyond change in habits and fear of using cash captured by other variables in the model.

Figure 1. Marginal Effects for the Key Explanatory Variables

A. Estimates from the *Cashless Switch* Model



B. Estimates from the *Cashless Intention* Model



Note: The plots show a prediction of probability that either *Cashless Switch* = 1 (panel A) or *Cashless Intention* = 1 (panel B) when one of the key explanatory variables is changed, while the remaining explanatory variables are kept constant at the sample average level. The vertical bars represent 95 percent confidence intervals. The graphs in panel A are derived based on logit regression (3) in Table 4, while panel B relied on regression (3) in Table 5.

Table 5 reports weighted logit estimates for models considering the intention to use more cashless transactions after the COVID-19 pandemic is over. The results indicate that COVID-induced fear of cash may have a long memory and is likely to extend into the distant future. Once again, *Change in Habits Related to Physical Contact* exhibits stronger statistical significance and has a larger marginal effect than *Change in Online Habits* (see panel B of Figure 1). Juxtaposition of the results with those contained in Table 4 reveals that the coefficients on the fear and change in habits variables are notably larger, which coheres with our expectations. Table 4 models actual changes in behavior, while Table 5 considers reported intentions to alter behavioral patterns in the future. Since forming an intention requires less effort on the part of the respondent than taking an actual action, the parameter estimates in Table 5 are expected to be larger.

Broadly speaking, a similar pattern of significance emerges across control variables. A slight discrepancy that could be noted is the weaker explanatory power of *Age* and *Shadow Economy*. It appears that older people, who are in the highest risk group, may be reluctant to increase the frequency of their cashless payments relative to the pandemic level after the health perils have dissipated. The diminished statistical significance of the shadow economy could reflect the fact that its future size is essentially unknown and, consequently, this variable plays a smaller role in shaping intentions. The protracted pandemic is expected to have a disproportionate effect on the informal economy, where workers without formalized contracts lack job security and do not benefit from furlough schemes (Webb, McQuaid, and Rand 2020).

The economic significance of the control variables can be assessed using the average marginal effects reported in our Appendix D. What can be gleaned from these estimates is that the variable with the most pronounced economic impact is *Cards & Mobile*, regardless of whether we model the *Cashless Switch* or *Cashless Intention*. The average marginal effect for *Literacy in Using Mobile Apps* proved large for the instantaneous increase in cashless payment frequency during the pandemic but was notably attenuated in the regression considering post-pandemic payment intentions. What mattered more from the point of view of agreement with the statement “After the pandemic, I will use cashless

Table 5. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over

	(1)	(2)	(3)
<i>Gender</i>	0.1980** (0.0787)	0.1606* (0.0829)	0.1772** (0.0843)
<i>Location Size</i>	0.0256 (0.0252)	0.0081 (0.0270)	0.0133 (0.0272)
<i>Age</i>	0.0023 (0.0026)	0.0054* (0.0029)	0.0046 (0.0029)
<i>Cards & Mobile</i>	0.5743*** (0.1431)	0.7547*** (0.1424)	0.7324*** (0.1438)
<i>Anonymity</i>	0.0087 (0.0346)	-0.1326*** (0.0384)	-0.1125*** (0.0391)
<i>Convenience of Cashless Payments</i>	0.0699 (0.0554)	0.0233 (0.0613)	0.0290 (0.0620)
<i>Safety of Cashless Payments</i>	0.2486*** (0.0629)	0.2768*** (0.0693)	0.2715*** (0.0700)
<i>Access to Cashless Payments Technologies</i>	0.0520 (0.0569)	-0.0876 (0.0639)	-0.0789 (0.0651)
<i>Ease of Use of Cashless Technologies</i>	0.1901*** (0.0635)	0.2330*** (0.0707)	0.2137*** (0.0717)
<i>Control over Finance with Cashless Payments</i>	0.1214** (0.0543)	0.0696 (0.0595)	0.0714 (0.0609)
<i>Literacy in Using Mobile Apps</i>	0.1517*** (0.0469)	0.1288** (0.0508)	0.1197** (0.0514)
<i>Experience in Using Computer Payments</i>	0.1186*** (0.0396)	0.0361 (0.0410)	0.0467 (0.0426)
<i>Experience in Using Mobile Payments</i>	0.0692 (0.0458)	0.0314 (0.0481)	0.0354 (0.0485)
<i>COVID Deaths</i>	0.0284*** (0.0074)	0.0169** (0.0077)	0.0187** (0.0077)
<i>Shadow Economy</i>	0.0105* (0.0059)	-0.0012 (0.0062)	-0.0021 (0.0063)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0005 (0.0025)	-0.0049* (0.0027)	-0.0036 (0.0028)
<i>Net Fear of Cash</i>	0.4408*** (0.0438)		0.3955*** (0.0472)
<i>Change in Habits Related to Physical Contact</i>		1.0063*** (0.0547)	0.9847*** (0.0551)
<i>Change in Online Habits</i>		0.1071** (0.0441)	0.1098** (0.0452)
Constant	-1.8385*** (0.2908)	-1.0840*** (0.3040)	-1.2423*** (0.3115)
Observations	5,504	5,504	5,504
chi2	395.6	537.4	550.6
p-value	0	0	0
McFadden's Pseudo R-squared	0.123	0.205	0.223

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

payments more often” was the safety of the cashless payment instruments.

6. Robustness Checks and Further Results

In order to confirm the validity of the story presented here, further tests and robustness checks were performed. To start with, we experimented with a different constellations and definitions of control variables. Firstly, the variable *Cards & Mobile* measuring the possession of any card, mobile, or wearable applicable at the point of sale was replaced with dummy variables categorizing respondents in accordance with their historical cash usage. The results displayed in Appendix E reveal a rational pattern of behavior. Individuals who made all of their transactions in cash prior to the pandemic were least likely to increase their frequency of cashless payments and showed least inclination to do so in the future. This is unsurprising, as the group includes people who operate in the shadow economy, are financially excluded, or have strong desire for anonymity. These attributes firmly anchor individuals’ desire to transact in cash. For the most part, the group that was most motivated to embrace more cashless transactions comprised respondents who historically used cash in 1 percent to 30 percent of their payments. Most importantly, inclusion of the past payment behavior dummies did not change our main conclusions regarding the key explanatory variables.

Secondly, we redefined our measurements of the five attributes of cashless payments (convenience, safety, access, ease of use, and control over finance). Instead of gauging them in absolute terms, we expressed them relative to the perceived characteristics of cash. Appendix F displays our findings which, once again, reaffirm the significance of fear and habit shifts in the formation of payment preferences.

Thirdly, we interrogated the question of whether the effect of the *Age* variable is linear. To this end, we converted the continuous *Age* variable into age-group dummies, which should allow us to pinpoint the age brackets in which respondents were particularly sensitive to COVID concerns (see Appendix G). The results indicate that individuals aged between 60 and 69 were particularly eager to increase the frequency of their cashless payments during the pandemic. Perhaps this could have been attributed to the fact that

COVID mortality within this age group was higher as compared to younger people. In terms of declaring an intention to increase frequency of cashless payments after the pandemic is over, respondents between the ages of 40 to 59 were particularly reluctant to do so.

Another point of inquiry arose from the reflection that respondents who already transacted exclusively cashless in the pre-pandemic period would have the tendency to rate different aspects of such transactions highly. At the same time, they were unable to increase their frequency of cashless payments, as they already resided at the limit. A question therefore arises as to whether our results are sensitive to the exclusion of such individuals. To probe this issue further, we constructed a sample which eliminated people who did not use cash at all in the 12 months preceding the survey ($n = 363$). We rerun the logit regressions on the restricted sample (see Appendix H) and note that our main inferences regarding the three key explanatory variables remain unaltered.

In the next step of our exploration, we investigated whether there are any country-specific factors that moderate the relationship between the COVID pandemic and respondents' willingness to switch to cashless transactions. For this purpose, we created eight dummies that were subsequently interacted with the three key explanatory variables in our study (*Net Fear of Cash* and the two change-in-habits variables). These dummies indicated countries with above-median values recorded for the EFT-POS terminals per thousand people, shadow economy size, COVID deaths, power distance and uncertainty avoidance index from the Hofstede national culture database, GDP per capita expressed in purchasing power parity prices, COVID stringency index measuring the severity of government policy responses, and countries that are Scandinavian. The estimates of logistic regressions imparting these interaction terms, along with their interpretation, are shown in Appendix I.

Finally, we consider an alternative approach to modeling our dichotomous variables by employing weighted probit models. Compared to the logit regressions used in our baseline regressions, this methodological framework makes different assumptions about the error term and is based on a different link function. Reassuringly, our results from this estimation reported in Appendix J corroborate our earlier conclusions, which is a testament to the fact that our inferences are not a mere byproduct of the methodology selected.

7. Practical Considerations

The first sphere that could be affected by the collective switch to cashless transactions is the banking sector. Such shift is positively affecting the profitability of banks in at least two ways. Firstly, payment services are an enduring element embedded in the core operations of commercial banks (Rambure and Nacamuli 2008) and allow them to augment and diversify their revenue streams. Historically, banks derived most of their revenues from acting as intermediaries that take deposits and lend money, earning net interest spread in the process. However, over time, non-interest income² became increasingly important (DeYoung and Rice 2004). Among the non-interest revenue streams are those attributable to processing and clearing payment transactions for various parties (Radecki 1999). According to the Federal Deposit Insurance Corporation (FDIC) about 33 percent of U.S. banks' income was classed as non-interest (Li et al. 2021). McKinsey and Company (2022) report that global payments revenues totaled \$2 trillion in 2019, increasing to \$2.1 trillion in 2021. These figures translate into a rise in the share of banking revenues from about 39 percent to 40 percent.

Secondly, adoption of electronic payment instruments bestows additional benefits upon banks in the form of reduced operating expenses, because the cost of electronic payment equals about one-third to one-half of the paper-based equivalent (Humphrey et al. 2006). Electronic payments are subject to economies of scale, which play a significant role in the unit costs of transactions incurred by banks (Beijnen and Bolt 2009; Bolt and Humphrey 2007; Khiaonarong 2003). These bank incentives are evinced by the rise of cashless branches in which withdrawals, deposits, or check-cashing services are unavailable (Engert and Fung 2019). Emergence of such bank offices is especially conspicuous in Sweden, where about 60 percent of branches had become cashless by 2016, forcing an even greater reduction in cash usage (Engert, Fung, and Segendorf 2020).

For FinTech firms (that is, innovative, technological companies providing financial services) change of payment habits could also have profound impact. Not only do they profit from launching

²That is, income arising from sources unconnected to the collection of interest payments (Haubrich and Young 2019).

and operationalizing digital payment innovations, but they are also actively involved in credit markets. Ghosh, Vallee, and Zeng (2021) argue that FinTechs consider cashless payments to be a good source of verifiable information regarding the creditworthiness of a borrower, which forces the prospective loan applicants to adopt them. The customer payment data is leveraged for alternative credit underwriting models in a novel way, creating economic incentives to move away from cash.

Global consultancy firm KPMG (2020) estimates that \$361 billion was invested in FinTechs during the 2017–19 period and 58 of those companies hit a valuation of more than \$1 billion, becoming so-called unicorns (McKinsey and Company 2020a). The momentous rise of FinTechs and their impact on transforming the financial industry's landscape is undisputed (Gomber et al. 2018; Thakor 2020). Interestingly, about \$144.4 billion of the above-mentioned total investment was channeled to companies providing payment services. These companies are referred to as PayTechs and compete with banks for their non-interest revenue streams. The population of PayTechs is growing continuously, with the number of companies that obtained regulatory licenses to provide such services in the European Union soaring from 350 in 2017 to 1,475 in 2020 (Polasik et al. 2020).

Evidence also seems to point to a surge in demand for products offered by FinTech and PayTech companies during the COVID-19 crisis. According to McKinsey and Company (2020b), 6 percent of U.S. consumers opened an overall banking FinTech account during the pandemic, while Fu and Mishra (2022) report a significant rise in downloads of finance mobile apps from Google and Apple app stores during this period. Interestingly, the epidemic-induced uptick in FinTech solutions was not uniformly distributed across countries, with a number of players in the sector struggling to raise funds and balancing precariously on the edge of insolvency (see, for instance, Chernova 2019; Kelly 2020; Kodoth 2020).

Our empirical analysis could be valuable to the banking sector, as well as FinTech and PayTech firms, because it provides a clear guidance for their future marketing efforts. More specifically, it helps to identify groups that are likely to use cashless payment services more frequently in the future and pinpoint attitudes that tend to promote such behavior. Firstly, our findings indicate that women declared

their willingness to increase the frequency of cashless payments more often than men. Advertising campaigns should be tailored accordingly to take full advantage of this fact. Furthermore, any promotions of digital payment instruments should endeavor to reassure the users about their safety. Our respondents attached great importance to this attribute. Similarly, ease of use of digital payment technologies proves to be a powerful stimulus for their adoption. For this reason, a deliberate effort should be undertaken to make the design of payment instruments/applications more user-friendly, without compromising their safety. Any advertising initiatives should also take account of the lasting changes in habits induced by the COVID pandemic and could perhaps attempt to reliably educate about the risk of contracting the virus via handling cash.

Another interesting result reported in this paper relates to the fact that the existence of shadow economy hindered the transition towards digital payments during the COVID-19 period, although this relationship was weaker for the reported future intentions. Vigorous actions of tax authorities and law enforcement agencies aimed at curbing the underground economic activities could potentially foster a more rapid move towards a cashless society. For many years, the shadow economy was perceived to be closely linked to cash transactions (Gordon 1990). Similarly, reduction in cash payments could have a discouraging effect on tax evasion and criminal activities. Zhang et al. (2019) find that an increase in the use of cashless payments helps to shrink and transform the shadow economy, while Schneider (2019) estimates that complete elimination of cash would decrease its size by 20.1 percent. With respect to tax compliance, two studies focusing on Greece and the euro area by Hondroyiannis and Papaoikonomou (2017, 2020) showed that that an increase in the share of card payments in private consumption led to a corresponding growth in VAT (value-added tax) revenues. For Greece, a 1 percentage point rise in this share was estimated to augment the VAT receipts by somewhere between 1 percent (Hondroyiannis and Papaoikonomou 2017) and 1.4 percent (Danchev, Gatopoulos, and Vettas 2020). Studies exploring this issue from the perspective of the whole European Union (most notably Immordino and Russo 2018 and Madzharova 2020) cohere with the conclusion that cashless payments tend to reduce VAT tax evasion.

Changes in how people pay are also critical for central banks, as these institutions are sole issuers of money and play a key role in its distribution. As shown in Subsection 2.2, the share of cash payments in retail transactions has decreased worldwide and transactional use of cash plunged even further during the COVID-19 epidemic. This, however, was eclipsed by precautionary hoarding of cash, which led to an increase in the overall demand for money (see, for instance, Caswell et al. 2020; Chen et al. 2020; Goodhart and Ashworth 2020; Kotkowski 2023). Whatever the demand, central banks need to be ready to provide an adequate supply of physical money at all times, in addition to performing their role as monetary authorities and safeguarding the financial system (Restoy 2020). This issuing obligation is especially important during times of distress, such as the COVID-19 pandemic, because failure to meet the surge in demand could heighten reputational risk. Additionally, central banks must be aware that the elevated demand would not last forever, and that they may be forced to withdraw and redeem some of the cash that is currently in circulation (Snellman, Vesala, and Humphrey 2001).

8. Conclusions

The coronavirus epidemic instilled a widespread sense of apprehension and changed the trajectories of our lives. In this paper, we examined how the disease outbreak affected consumer choices regarding payment methods at the point of sale. The results clearly indicate that those who believed that cash poses a relatively high risk of viral transmission opted for cashless alternatives. Payment behavior was also indirectly transmuted through the impact that the pandemic had on the patterns of our daily activities. Especially, our altered habitual conduct in physical spaces exerted a powerful influence, steering individuals towards cashless transactions. The drift away from physical currency was also attributable to changes in online behavior, albeit to a lesser degree. Interestingly, the possibility of contagion through cash and transformed habits not only drove the contemporaneous switch between the payment instruments but also imprinted themselves on respondents' future intentions to transact in a cashless manner, even after the COVID pandemic has been contained.

Our findings have several practical implications relevant to every link in the chain of payment transaction processing. Banks, acquirers, FinTechs, and payment organizations must be aware that COVID-like events can drastically change the volume and value of processed transactions. While in some cases it may bring a much-needed revenue stream, it also puts a strain on available resources. Failure to meet the surge in demand could heighten reputational risk. Similarly, merchants need to show flexibility in times perturbed by fear of disease contagion and dynamically evolving consumer habits. Preferred payment options should be offered to paying patrons to alleviate their anxiety. Furthermore, central banks should carry out further studies on the epidemiological safety of different payment instruments, so conclusive knowledge about this phenomenon could emerge and potentially ease angst within the population. Finally, the COVID-induced speedy move towards digital payments has the potential to disadvantage those who are financially excluded, particularly immigrants, elderly, unemployed, or disabled people. This area of concern warrants further scientific inquiry in the future.

Appendix A

Table A.1. Internet Use in Our Sample Countries in 2020

	Individuals Who Used Internet in the Last 12 Months (in %)	Individuals Who Have Ever Used the Internet (in %)	Population
Austria	89	92	8,917,205
Belgium	92	94	11,555,997
Bulgaria	74	79	6,934,015
Czech Republic	89	92	10,698,896
Denmark	99	99	5,831,404
Finland	97	98	5,530,719
France*	91	93	67,391,582
Germany	95	96	83,240,525
Greece	79	80	10,715,549
Hungary	86	88	9,749,763
Ireland	92	94	4,994,724
Italy	81	84	59,554,023
Lithuania	84	86	2,794,700
Netherlands	95	96	17,441,139
Norway	98	99	5,379,475
Poland	85	87	37,950,802
Portugal	79	82	10,305,564
Romania	85	86	19,286,123
Slovak Republic	91	93	5,458,827
Spain	93	94	47,351,567
Sweden	97	98	10,353,442
United Kingdom	98	98	67,215,293
Population-Weighted Average	90.5035	92.0413	
<p>*Due to the lack of data, we use 2019 statistics for France. Note: Internet use data are sourced from Eurostat, while the population data come from WDI. Survey consists of all individuals aged 16 to 74. On an optional basis, some countries collect separate data on other age groups: individuals aged 15 years or less, aged 75 or more.</p>			

Appendix B

Table B.1. Country-Level Averages for the Key Variables

	<i>Cashless Switch</i>	<i>Cashless Intention</i>	<i>Net Fear of Cash</i>	<i>Change in Habits Related to Physical Contact</i>	<i>Change in Online Habits</i>
Austria	0.39	0.28	0.06	-0.24	-0.14
Belgium	0.63	0.48	0.32	0.01	0.08
Bulgaria	0.29	0.34	0.28	0.17	0.01
Czech Republic	0.43	0.35	0.25	-0.15	-0.02
Denmark	0.42	0.34	0.41	-0.18	-0.10
Finland	0.41	0.38	0.16	-0.13	-0.01
France	0.42	0.37	0.14	-0.05	0.01
Germany	0.34	0.31	0.09	-0.22	-0.21
Greece	0.47	0.33	0.03	-0.18	0.12
Hungary	0.34	0.39	0.37	-0.10	-0.21
Ireland	0.63	0.51	0.35	0.20	0.06
Italy	0.40	0.38	0.10	0.23	-0.05
Lithuania	0.31	0.39	0.22	-0.08	0.01
Netherlands	0.56	0.38	0.18	-0.10	0.14
Norway	0.47	0.38	0.11	-0.22	-0.07
Poland	0.56	0.53	0.44	0.09	0.07
Portugal	0.61	0.57	0.31	0.35	0.07
Romania	0.55	0.55	0.39	0.43	0.00
Slovakia	0.39	0.33	0.23	-0.15	0.08
Spain	0.49	0.48	0.04	0.23	0.03
Sweden	0.32	0.29	0.20	-0.24	-0.07
United Kingdom	0.65	0.53	0.30	0.17	0.14

Appendix C. Exploring the Data

To investigate the issue of overlap in respondents' answers, we present in Table C.1 the data on joint distribution of the two dependent variables used in our study.

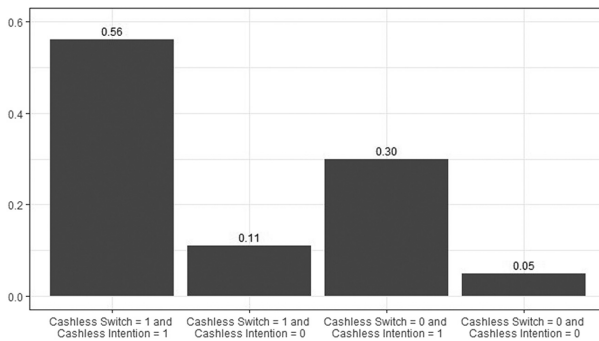
We have also examined whether the summary statistics for each of the four cohorts defined by the cells in the table above are comparable and have discovered the most pronounced differences occur for the variable *Net Fear of Cash*. Figure C.1 plots these values. This

Table C.1. Joint Distribution of the Two Dependent Variables

	<i>Cashless Intention</i> = 0	<i>Cashless Intention</i> = 1	Total
<i>Cashless Switch</i> = 0	41.12% (2,263)	12.17% (670)	53.29% (2,933)
<i>Cashless Switch</i> = 1	17.48% (962)	29.23% (1,609)	46.71% (2,571)
Total	58.59% (3,225)	41.41% (2,279)	100.00% (5,504)

Note: This table presents the joint distribution of *Cashless Switch* and *Cashless Intention*. The numbers presented show the proportion of the sample and the number of observations falling within a particular category in parentheses.

Figure C.1. Average *Net Fear of Cash* in Different Cohorts



Note: This figure presents averages for the variable *Net Fear of Cash* in four groups defined by their values of *Cashless Switch* and *Cashless Intention*.

discovery aligns well with the story that is being told in our paper, namely that the fear of COVID transmission through cash drives the payment choices of respondents.

Appendix D

Table D.1. Average Marginal Effects for Control Variables

	Table 4 Column 3	Table 5 Column 4
<i>Gender</i>	0.0376	0.0387
<i>Location Size</i>	0.0051	0.0044
<i>Age</i>	0.0011	0.0007
<i>Cards & Mobile</i>	0.1521	0.1259
<i>Anonymity</i>	-0.0160	-0.0034
<i>Convenience of Cashless Payments</i>	0.0005	0.0125
<i>Safety of Cashless Payments</i>	0.0293	0.0549
<i>Access to Cashless Payments Technologies</i>	0.0043	0.0089
<i>Ease of Use of Cashless Technologies</i>	0.0365	0.0440
<i>Control over Finance with Cashless Technologies</i>	0.0041	0.0267
<i>Literacy in Using Mobile Apps</i>	0.0850	0.0346
<i>Experience in Using Computer Payments</i>	0.133	0.0236
<i>Experience in Using Mobile Payments</i>	0.0091	0.0141
<i>COVID Deaths</i>	0.0053	0.0056
<i>Shadow Economy</i>	-0.0026	0.0025
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0005	-0.0002

Note: This table reports average marginal effects for the control variables in logit regressions presented in Table 4 (column 3) and Table 5 (column 3).

Appendix E. Examining the Importance of Historical Cash Usage

In this appendix we attempt to assess the importance of historical cash usage in determining *Cashless Switch* and *Cashless Intention*. Our questionnaire allows us to measure the past use of cash (and by implication cashless instruments), as it includes an item phrased as follows:

Table E.1. Dummy Variables

Variables		No. of Cases
CASH_0	0% of the Payments Made by Cash	363
CASH_30	From 1% to 30% of the Payments Made by Cash	2,901
CASH_60	From 31% to 60% of the Payments Made by Cash	1,217
CASH_99	From 61% to 99% of the Payments Made by Cash	575
CASH_100	100% of the Payments Made by Cash	448

What was the share of individual payment methods in your purchases in physical stores and service outlets in the last 12 months?

[Please specify the shares in the number of transactions, not the value. The selected answers should add up to approximately 100%.]

From the responses recorded, we were able to obtain data on intensity of cash utilization, which was divided into five brackets. These were later transformed into dummy variables, as shown in Table E.1.

Subsequently, these dummies were entered into our logit regressions, while simultaneously excluding the *Cards & Mobile* dummy in order to alleviate any multicollinearity concerns. In a similar vein, one of the dummies (CASH_99) is omitted to circumvent the perfect multicollinearity problem. The results are presented in Tables E.2 and E.3.

Table E.2. Modeling the Switch to Cashless Payments during the Pandemic (including past payment behavior)

	(1)	(2)	(3)
<i>Gender</i>	0.1655** (0.0775)	0.1415* (0.0787)	0.1477* (0.0790)
<i>Location Size</i>	0.0357 (0.0250)	0.0257 (0.0255)	0.0284 (0.0257)
<i>Age</i>	0.0039 (0.0026)	0.0056** (0.0027)	0.0053** (0.0027)
<i>Anonymity</i>	-0.0226 (0.0339)	-0.0920*** (0.0351)	-0.0808** (0.0352)

(continued)

Table E.2. (Continued)

	(1)	(2)	(3)
<i>Convenience of Cashless Payments</i>	-0.0116 (0.0543)	-0.0404 (0.0565)	-0.0371 (0.0566)
<i>Safety of Cashless Payments</i>	0.0875 (0.0608)	0.0891 (0.0614)	0.0816 (0.0622)
<i>Access to Cashless Payments Technologies</i>	0.0250 (0.0536)	-0.0393 (0.0555)	-0.0323 (0.0557)
<i>Ease of Use of Cashless Technologies</i>	0.1551** (0.0614)	0.1739*** (0.0626)	0.1650*** (0.0629)
<i>Control over Finance with Cashless Payments</i>	0.0061 (0.0547)	-0.0301 (0.0553)	-0.0329 (0.0561)
<i>Literacy in Using Mobile Apps</i>	0.3421*** (0.0479)	0.3313*** (0.0480)	0.3312*** (0.0483)
<i>Experience in Using Computer Payments</i>	0.0755** (0.0373)	0.0333 (0.0378)	0.0374 (0.0380)
<i>Experience in Using Mobile Payments</i>	0.0216 (0.0453)	0.0004 (0.0471)	0.0041 (0.0466)
<i>COVID Deaths</i>	0.0211*** (0.0073)	0.0145* (0.0076)	0.0154** (0.0076)
<i>Shadow Economy</i>	-0.0097* (0.0059)	-0.0154*** (0.0059)	-0.0165*** (0.0060)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0030 (0.0025)	0.0004 (0.0026)	0.0012 (0.0026)
<i>Net Fear of Cash</i>	0.2615*** (0.0391)		0.2232*** (0.0398)
<i>Change in Habits Related to Physical Contact</i>		0.4739*** (0.0428)	0.4533*** (0.0429)
<i>Change in Online Habits</i>		0.0736* (0.0400)	0.0753* (0.0401)
CASH_0	0.6380*** (0.1903)	0.5973*** (0.1898)	0.5477*** (0.1938)
CASH_30	1.0890*** (0.1337)	1.0979*** (0.1361)	1.0739*** (0.1370)
CASH_60	0.8344*** (0.1420)	0.8203*** (0.1453)	0.8308*** (0.1463)
CASH_100	-0.1690 (0.1891)	-0.2671 (0.1907)	-0.2335 (0.1920)
Constant	-1.3766*** (0.2892)	-0.8782*** (0.2980)	-0.9617*** (0.2993)
Observations	5,504	5,504	5,504
chi2	415.1	446.6	477.4
p-value	0	0	0
McFadden's Pseudo R-squared	0.109	0.129	0.136
Note: This table reports regression coefficients of weighted logit regressions in which <i>Cashless Switch</i> acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.			

Table E.3. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (including past payment behavior)

	(1)	(2)	(3)
<i>Gender</i>	0.1780** (0.0804)	0.1435* (0.0849)	0.1578* (0.0860)
<i>Location Size</i>	0.0322 (0.0253)	0.0163 (0.0273)	0.0196 (0.0276)
<i>Age</i>	0.0012 (0.0027)	0.0039 (0.0030)	0.0032 (0.0030)
<i>Anonymity</i>	0.0544 (0.0356)	-0.0916** (0.0395)	-0.0770* (0.0400)
<i>Convenience of Cashless Payments</i>	0.0501 (0.0569)	0.0092 (0.0623)	0.0129 (0.0631)
<i>Safety of Cashless Payments</i>	0.2231*** (0.0634)	0.2458*** (0.0699)	0.2436*** (0.0706)
<i>Access to Cashless Payments Technologies</i>	0.0469 (0.0563)	-0.0849 (0.0652)	-0.0759 (0.0661)
<i>Ease of Use of Cashless Technologies</i>	0.1948*** (0.0654)	0.2416*** (0.0725)	0.2252*** (0.0740)
<i>Control over Finance with Cashless Payments</i>	0.1198** (0.0565)	0.0545 (0.0614)	0.0569 (0.0631)
<i>Literacy in Using Mobile Apps</i>	0.1072** (0.0485)	0.0807 (0.0524)	0.0740 (0.0532)
<i>Experience in Using Computer Payments</i>	0.1193*** (0.0401)	0.0432 (0.0423)	0.0507 (0.0432)
<i>Experience in Using Mobile Payments</i>	0.0293 (0.0468)	-0.0063 (0.0498)	-0.0005 (0.0499)
<i>COVID Deaths</i>	0.0260*** (0.0074)	0.0152* (0.0078)	0.0169** (0.0078)
<i>Shadow Economy</i>	0.0171*** (0.0061)	0.0064 (0.0065)	0.0052 (0.0065)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0005 (0.0027)	-0.0047* (0.0028)	-0.0034 (0.0029)
<i>Net Fear of Cash</i>	0.4185*** (0.0439)		0.3702*** (0.0473)
<i>Change in Habits Related to Physical Contact</i>		1.0197*** (0.0552)	0.9985*** (0.0557)
<i>Change in Online Habits</i>		0.0772* (0.0449)	0.0800* (0.0460)
CASH_0	1.1021*** (0.2043)	1.1036*** (0.2210)	1.0491*** (0.2283)
CASH_30	1.2600*** (0.1492)	1.3722*** (0.1553)	1.3461*** (0.1587)
CASH_60	0.7843*** (0.1574)	0.7808*** (0.1645)	0.7989*** (0.1676)

(continued)

Table E.3. (Continued)

	(1)	(2)	(3)
CASH_100	0.1125 (0.2048)	-0.0596 (0.2100)	-0.0039 (0.2132)
Constant	-2.4349*** (0.3086)	-1.5902*** (0.3249)	-1.7295*** (0.3299)
Observations	5,504	5,504	5,504
chi2	503.1	630.1	642.3
p-value	0	0	0
McFadden's Pseudo R-squared	0.146	0.230	0.245
<p>Note: This table reports regression coefficients of weighted logit regressions in which <i>Cashless Intention</i> acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.</p>			

Appendix F. Measuring Cashless Payments Attributes Relative to Cash

In the main body of our paper, we have quantified different aspects of cashless payments (convenience, safety, access, ease of use, and control over finance) using factor analysis. This is because we needed to aggregate information on a multitude of payment technologies. The resultant variables were absolute measures, in the sense that they pertained to the cashless technologies alone.

In this appendix we produce regressions where these characteristics are expressed in relative terms. In other words, the attributes of cashless instruments were compared to those of cash. A critical issue that needs to be elucidated here is the procedure that was followed to construct these relative measures. It can be broken into two distinct steps:

- (i) For any given payment characteristic (e.g., convenience or safety), we calculate the score differences between each of the six payment instruments (payment cards; HCE payments; Google Pay, Apple Pay, QR, wearables) and cash.
- (ii) Factor analysis is then deployed to aggregate the score differences across all payment instruments.

In the regressions that follow (Tables F.1 and F.2), we add the word “Net” in front of a payment characteristic to highlight the fact that it has been calculated relative to cash.

Table F.1. Modeling the Switch to Cashless Payments during the Pandemic (net constructs)

	(1)	(2)	(3)
<i>Gender</i>	0.1776** (0.0765)	0.1483* (0.0776)	0.1558** (0.0779)
<i>Location Size</i>	0.0287 (0.0250)	0.0184 (0.0255)	0.0215 (0.0256)
<i>Age</i>	0.0060** (0.0025)	0.0070*** (0.0026)	0.0067** (0.0026)

(continued)

Table F.1. (Continued)

	(1)	(2)	(3)
<i>Cards & Mobile</i>	0.6598*** (0.1310)	0.7166*** (0.1330)	0.7073*** (0.1330)
<i>Anonymity</i>	-0.0174 (0.0341)	-0.0943*** (0.0352)	-0.0824** (0.0353)
<i>Net Convenience of Cashless Payments</i>	-0.1688*** (0.0512)	-0.1895*** (0.0522)	-0.1678*** (0.0527)
<i>Net Safety of Cashless Payments</i>	0.1660*** (0.0534)	0.1401** (0.0544)	0.1375** (0.0549)
<i>Net Access to Cashless Payments Technologies</i>	-0.0117 (0.0503)	-0.0935* (0.0506)	-0.0736 (0.0514)
<i>Net Ease of Use of Cashless Technologies</i>	0.0511 (0.0565)	0.0448 (0.0574)	0.0332 (0.0578)
<i>Net Control over Finance with Cashless Payments</i>	0.0136 (0.0475)	-0.0047 (0.0484)	-0.0051 (0.0487)
<i>Literacy in Using Mobile Apps</i>	0.3682*** (0.0468)	0.3556*** (0.0470)	0.3548*** (0.0473)
<i>Experience in Using Computer Payments</i>	0.0688* (0.0357)	0.0249 (0.0365)	0.0282 (0.0369)
<i>Experience in Using Mobile Payments</i>	0.0486 (0.0438)	0.0204 (0.0454)	0.0231 (0.0452)
<i>COVID Deaths</i>	0.0203*** (0.0072)	0.0139* (0.0074)	0.0150** (0.0074)
<i>Shadow Economy</i>	-0.0156*** (0.0058)	-0.0229*** (0.0059)	-0.0233*** (0.0059)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0033 (0.0025)	0.0008 (0.0026)	0.0016 (0.0026)
<i>Net Fear of Cash</i>	0.2708*** (0.0391)		0.2308*** (0.0399)
<i>Change in Habits Related to Physical Contact</i>		0.4739*** (0.0421)	0.4520*** (0.0422)
<i>Change in Online Habits</i>		0.0711* (0.0397)	0.0723* (0.0398)
Constant	-1.1584*** (0.2834)	-0.6335** (0.2891)	-0.7352** (0.2913)
Observations	5,504	5,504	5,504
chi2	357.5	406.0	440.7
p-value	0	0	0
McFadden's Pseudo R-squared	0.093	0.112	0.120

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table F.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (net constructs)

	(1)	(2)	(3)
<i>Gender</i>	0.1922** (0.0789)	0.1496* (0.0833)	0.1639* (0.0844)
<i>Location Size</i>	0.0299 (0.0252)	0.0116 (0.0271)	0.0162 (0.0272)
<i>Age</i>	0.0038 (0.0027)	0.0054* (0.0028)	0.0047 (0.0029)
<i>Cards & Mobile</i>	0.5695*** (0.1411)	0.7256*** (0.1425)	0.7111*** (0.1427)
<i>Anonymity</i>	0.0727** (0.0353)	-0.0902** (0.0390)	-0.0739* (0.0393)
<i>Net Convenience of Cashless Payments</i>	-0.3054 (0.0516)	-0.3796 (0.0585)	-0.3457 (0.0589)
<i>Net Safety of Cashless Payments</i>	0.1512*** (0.0556)	0.1051* (0.0604)	0.1066* (0.0615)
<i>Net Access to Cashless Payments Technologies</i>	-0.0147 (0.0519)	-0.1826 (0.0562)	-0.1505 (0.0570)
<i>Net Ease of Use of Cashless Technologies</i>	0.1127* (0.0582)	0.1090* (0.0635)	0.0899 (0.0646)
<i>Net Control over Finance with Cashless Payments</i>	0.1176** (0.0482)	0.0937* (0.0544)	0.0985* (0.0546)
<i>Literacy in Using Mobile Apps</i>	0.1468*** (0.0478)	0.1207** (0.0511)	0.1148** (0.0516)
<i>Experience in Using Computer Payments</i>	0.1442*** (0.0402)	0.0639 (0.0408)	0.0711* (0.0426)
<i>Experience in Using Mobile Payments</i>	0.1088** (0.0461)	0.0628 (0.0473)	0.0680 (0.0478)
<i>COVID Deaths</i>	0.0223*** (0.0074)	0.0113 (0.0077)	0.0133* (0.0078)
<i>Shadow Economy</i>	0.0076 (0.0059)	-0.0068 (0.0063)	-0.0071 (0.0063)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0010 (0.0026)	-0.0042 (0.0028)	-0.0030 (0.0028)
<i>Net Fear of Cash</i>	0.4267*** (0.0438)		0.3741*** (0.0478)
<i>Change in Habits Related to Physical Contact</i>		1.0339*** (0.0555)	1.0110*** (0.0559)
<i>Change in Online Habits</i>		0.0736* (0.0444)	0.0759* (0.0453)
Constant	-1.9791*** (0.2908)	-1.0295*** (0.3041)	-1.1886*** (0.3094)
Observations	5,504	5,504	5,504
chi2	412.0	544.3	553.6
p-value	0	0	0
McFadden's Pseudo R-squared	0.119	0.207	0.223

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix G

Table G.1. Modeling the Switch to Cashless Payments during the Pandemic (age brackets)

	(1)	(2)	(3)
<i>Gender</i>	0.1722** (0.0762)	0.1488* (0.0773)	0.1548** (0.0778)
<i>Location Size</i>	0.0247 (0.0249)	0.0139 (0.0253)	0.0175 (0.0255)
<i>Age < 30</i>	-0.0830 (0.1649)	-0.1504 (0.1686)	-0.1187 (0.1692)
<i>Age >= 30 and < 40</i>	-0.0949 (0.1653)	-0.2115 (0.1686)	-0.1697 (0.1696)
<i>Age >= 40 and < 50</i>	0.0953 (0.1589)	0.0413 (0.1624)	0.0744 (0.1625)
<i>Age >= 50 and < 60</i>	-0.0289 (0.1604)	-0.0275 (0.1622)	-0.0141 (0.1634)
<i>Age >= 60 and < 70</i>	0.2033 (0.1547)	0.0070*** (0.0026)	0.0067** (0.0026)
<i>Cards & Mobile</i>	0.6639*** (0.1324)	0.7404*** (0.1339)	0.7244*** (0.1340)
<i>Anonymity</i>	-0.0563* (0.0337)	-0.1240*** (0.0348)	-0.1094*** (0.0351)
<i>Convenience of Cashless Payments</i>	0.0067 (0.0537)	-0.0258 (0.0562)	-0.0215 (0.0564)
<i>Safety of Cashless Payments</i>	0.1214** (0.0595)	0.1257** (0.0601)	0.1158* (0.0607)
<i>Access to Cashless Payments Technologies</i>	0.0228 (0.0535)	-0.0447 (0.0547)	-0.0376 (0.0552)
<i>Ease of Use of Cashless Technologies</i>	0.1514** (0.0600)	0.1698*** (0.0616)	0.1592*** (0.0616)
<i>Control over Finance with Cashless Payments</i>	0.0135 (0.0529)	-0.0176 (0.0538)	-0.0209 (0.0544)
<i>Literacy in Using Mobile Apps</i>	0.3771*** (0.0466)	0.3660*** (0.0469)	0.3639*** (0.0472)
<i>Experience in Using Computer Payments</i>	0.0652* (0.0360)	0.0200 (0.0369)	0.0253 (0.0372)
<i>Experience in Using Mobile Payments</i>	0.0444 (0.0442)	0.0209 (0.0460)	0.0230 (0.0458)
<i>COVID Deaths</i>	0.0241*** (0.0072)	0.0170** (0.0075)	0.0178** (0.0075)
<i>Shadow Economy</i>	-0.0139** (0.0057)	-0.0199*** (0.0058)	-0.0209*** (0.0059)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0032 (0.0025)	0.0003 (0.0026)	0.0013 (0.0026)
<i>Net Fear of Cash</i>	0.2844*** (0.0390)		0.2459*** (0.0398)
<i>Change in Habits Related to Physical Contact</i>		0.4777*** (0.0420)	0.4554*** (0.0421)

(continued)

Table G.1. (Continued)

	(1)	(2)	(3)
<i>Change in Online Habits</i>		0.0952** (0.0394)	0.0951** (0.0395)
Constant	-0.8453*** (0.2801)	-0.2807 (0.2852)	-0.4228 (0.2870)
Observations	5,504	5,504	5,504
chi2	350.5	401.6	440.6
p-value	0	0	0
McFadden's Pseudo R-squared	0.0895	0.110	0.118

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. In these models, the dummy for individuals aged 70 and over is excluded and, consequently, this group acts as a benchmark. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table G.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (age brackets)

	(1)	(2)	(3)
<i>Gender</i>	0.1973** (0.0788)	0.1593* (0.0829)	0.1745** (0.0843)
<i>Location Size</i>	0.0222 (0.0253)	0.0056 (0.0271)	0.0103 (0.0273)
<i>Age < 30</i>	-0.1573 (0.1663)	-0.2533 (0.1794)	-0.1952 (0.1813)
<i>Age >= 30 and < 40</i>	-0.0453 (0.1622)	-0.2357 (0.1748)	-0.1645 (0.1751)
<i>Age >= 40 and < 50</i>	-0.2829* (0.1604)	-0.3789** (0.1712)	-0.3258* (0.1720)
<i>Age >= 50 and < 60</i>	-0.3640** (0.1621)	-0.3714** (0.1732)	-0.3543** (0.1750)
<i>Age >= 60 and < 70</i>	0.0076 (0.1549)	-0.0150 (0.1651)	0.0387 (0.1668)
<i>Cards & Mobile</i>	0.5699*** (0.1433)	0.7454*** (0.1430)	0.7224*** (0.1442)
<i>Anonymity</i>	0.0127 (0.0348)	-0.1285*** (0.0386)	-0.1084*** (0.0393)

(continued)

Table G.2. (Continued)

	(1)	(2)	(3)
<i>Convenience of Cashless Payments</i>	0.0701 (0.0555)	0.0264 (0.0615)	0.0304 (0.0621)
<i>Safety of Cashless Payments</i>	0.2607*** (0.0633)	0.2839*** (0.0696)	0.2805*** (0.0705)
<i>Access to Cashless Payments Technologies</i>	0.0518 (0.0571)	-0.0873 (0.0639)	-0.0788 (0.0652)
<i>Ease of Use of Cashless Technologies</i>	0.1919*** (0.0636)	0.2355*** (0.0707)	0.2165*** (0.0718)
<i>Control over Finance with Cashless Payments</i>	0.1103** (0.0545)	0.0590 (0.0599)	0.0598 (0.0615)
<i>Literacy in Using Mobile Apps</i>	0.1522*** (0.0470)	0.1263** (0.0511)	0.1177** (0.0517)
<i>Experience in Using Computer Payments</i>	0.1134*** (0.0392)	0.0325 (0.0408)	0.0427 (0.0423)
<i>Experience in Using Mobile Payments</i>	0.0615 (0.0460)	0.0270 (0.0480)	0.0297 (0.0485)
<i>COVID Deaths</i>	0.0286*** (0.0074)	0.0172** (0.0077)	0.0190** (0.0078)
<i>Shadow Economy</i>	0.0105* (0.0059)	-0.0012 (0.0062)	-0.0022 (0.0063)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0006 (0.0026)	-0.0048* (0.0028)	-0.0034 (0.0028)
<i>Net Fear of Cash</i>	0.4448*** (0.0435)		0.3981*** (0.0469)
<i>Change in Habits Related to Physical Contact</i>		1.0052*** (0.0547)	0.9827*** (0.0551)
<i>Change in Online Habits</i>		0.1127** (0.0445)	0.1150** (0.0456)
Constant	-1.5871*** (0.2807)	-0.6104** (0.2987)	-0.8494*** (0.3026)
Observations	5,504	5,504	5,504
chi2	407.0	534.6	552.7
p-value	0	0	0
McFadden's Pseudo R-squared	0.125	0.206	0.225
<p>Note: This table reports regression coefficients of weighted logit regressions in which <i>Cashless Intention</i> acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. In these models, the dummy for individuals aged 70 and over is excluded and, consequently, this group acts as a benchmark. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.</p>			

Appendix H

Table H.1. Modeling the Switch to Cashless Payments during the Pandemic (cash users only)

	(1)	(2)	(3)
<i>Gender</i>	0.1543* (0.0787)	0.1290 (0.0797)	0.1361* (0.0802)
<i>Location Size</i>	0.0217 (0.0257)	0.0099 (0.0262)	0.0150 (0.0263)
<i>Age</i>	0.0041 (0.0026)	0.0061** (0.0027)	0.0056** (0.0027)
<i>Cards & Mobile</i>	0.6548*** (0.1359)	0.7256*** (0.1367)	0.7133*** (0.1370)
<i>Anonymity</i>	-0.0832** (0.0349)	-0.1440*** (0.0358)	-0.1301*** (0.0361)
<i>Convenience of Cashless Payments</i>	0.0052 (0.0552)	-0.0295 (0.0576)	-0.0231 (0.0578)
<i>Safety of Cashless Payments</i>	0.0803 (0.0618)	0.0953 (0.0628)	0.0773 (0.0631)
<i>Access to Cashless Payments Technologies</i>	0.0286 (0.0554)	-0.0338 (0.0566)	-0.0287 (0.0570)
<i>Ease of Use of Cashless Technologies</i>	0.1697*** (0.0626)	0.1865*** (0.0640)	0.1780*** (0.0641)
<i>Control over Finance with Cashless Payments</i>	0.0215 (0.0552)	-0.0125 (0.0560)	-0.0136 (0.0567)
<i>Literacy in Using Mobile Apps</i>	0.3890*** (0.0489)	0.3802*** (0.0490)	0.3763*** (0.0493)
<i>Experience in Using Computer Payments</i>	0.0469 (0.0369)	-0.0013 (0.0372)	0.0029 (0.0377)
<i>Experience in Using Mobile Payments</i>	0.0371 (0.0452)	0.0133 (0.0466)	0.0156 (0.0465)
<i>COVID Deaths</i>	0.0258*** (0.0073)	0.0191** (0.0076)	0.0198*** (0.0076)
<i>Shadow Economy</i>	-0.0131** (0.0058)	-0.0191*** (0.0059)	-0.0200*** (0.0060)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0024 (0.0025)	-0.0004 (0.0026)	0.0006 (0.0026)
<i>Net Fear of Cash</i>	0.2936*** (0.0408)		0.2605*** (0.0419)
<i>Change in Habits Related to Physical Contact</i>		0.4597*** (0.0437)	0.4385*** (0.0438)
<i>Change in Online Habits</i>		0.0959** (0.0404)	0.0980** (0.0406)
Constant	-0.9015*** (0.2915)	-0.4926* (0.2969)	-0.5932** (0.2995)
Observations	5,141	5,141	5,141
chi2	323.1	362.8	398.1
p-value	0	0	0
McFadden's Pseudo R-squared	0.089	0.106	0.115

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table H.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (cash users only)

	(1)	(2)	(3)
<i>Gender</i>	0.1886** (0.0814)	0.1461* (0.0860)	0.1627* (0.0873)
<i>Location Size</i>	0.0212 (0.0263)	0.0028 (0.0281)	0.0089 (0.0285)
<i>Age</i>	0.0026 (0.0027)	0.0059** (0.0030)	0.0050 (0.0030)
<i>Cards & Mobile</i>	0.5979*** (0.1477)	0.7745*** (0.1442)	0.7606*** (0.1459)
<i>Anonymity</i>	-0.0159 (0.0360)	-0.1526*** (0.0397)	-0.1351*** (0.0404)
<i>Convenience of Cashless Payments</i>	0.0629 (0.0578)	0.0128 (0.0638)	0.0198 (0.0647)
<i>Safety of Cashless Payments</i>	0.2651*** (0.0666)	0.3123*** (0.0732)	0.2968*** (0.0741)
<i>Access to Cashless Payments Technologies</i>	0.0757 (0.0591)	-0.0550 (0.0666)	-0.0488 (0.0682)
<i>Ease of Use of Cashless Technologies</i>	0.2033*** (0.0663)	0.2441*** (0.0736)	0.2294*** (0.0750)
<i>Control over Finance with Cashless Payments</i>	0.1091* (0.0569)	0.0468 (0.0621)	0.0524 (0.0641)
<i>Literacy in Using Mobile Apps</i>	0.1412*** (0.0489)	0.1168** (0.0530)	0.1053** (0.0536)
<i>Experience in Using Computer Payments</i>	0.1101*** (0.0404)	0.0204 (0.0416)	0.0287 (0.0436)
<i>Experience in Using Mobile Payments</i>	0.0668 (0.0472)	0.0326 (0.0494)	0.0358 (0.0500)
<i>COVID Deaths</i>	0.0279*** (0.0075)	0.0166** (0.0079)	0.0181** (0.0079)
<i>Shadow Economy</i>	0.0087 (0.0061)	-0.0037 (0.0064)	-0.0046 (0.0065)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0008 (0.0026)	-0.0046 (0.0028)	-0.0031 (0.0028)
<i>Net Fear of Cash</i>	0.4474*** (0.0460)		0.4104*** (0.0492)
<i>Change in Habits Related to Physical Contact</i>		1.0185*** (0.0570)	1.0005*** (0.0577)
<i>Change in Online Habits</i>		0.1126** (0.0458)	0.1181** (0.0473)
Constant	-1.7559*** (0.3007)	-1.0091*** (0.3152)	-1.1621*** (0.3202)
Observations	5,141	5,141	5,141
chi2	382.7	531.8	539.0
p-value	0	0	0
McFadden's Pseudo R-squared	0.125	0.208	0.227

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix I. Moderating Effects

In this appendix we investigate whether interaction models could inform us about country-level factors that moderate the relationship between the COVID pandemic and the willingness to switch to cashless payments. Eight different variables are considered as possible moderating factors, which are subsequently interacted in our logistic regressions with *Net Fear of Cash* and the two changes in habits variables. To ease the task of interpretation and alleviate multicollinearity concerns, these eight variables are constructed as dummies that partition our sample into two groups—one in which a given characteristic exists or is prominent (i.e., records an above-median value) and one in which it is not. Three binary indicators were constructed from variables already used in our main analysis, namely *COVID Deaths*, *Shadow Economy*, and *Number of EFT-POS Terminals per Thousand People*, whereas two additional dummies derive from country scores for power distance and uncertainty avoidance index retrieved from the Hofstede national culture data set. Another two dichotomous variables split the sample into Scandinavian and non-Scandinavian countries, as well as developed versus emerging economies based on the value of GDP per capita in 2020 measured at purchasing power parity prices. The GDP data were sourced from the World Development Indicators database maintained by the World Bank. Finally, we split the countries according to their COVID stringency index, which measures the severity of policy responses to COVID-19 pandemic and was compiled by Mathieu et al. (2020). The values of the stringency index were averaged during the July to August 2020 period, which covers the timeframe when the survey was conducted. Table I.1 catalogues and describes the interaction dummies.

Table I.2 presents logit regressions with interaction terms that model the decision to pay cashless more often during the COVID pandemic.

As there are as many as 24 interaction terms across the eight regressions in the table above, we restrict ourselves to analyzing only those that are statistically significant at the 5 percent level or better. Firstly, the interaction between the Scandinavian country dummy and *Net Fear of Cash* bears a negative coefficient and proves meaningful to the choice of cashless payments during the COVID

Table I.1. Definitions of Variables

Variable	Definition
<i>D_Scand</i>	A dummy variable taking a value of one if the respondent resides in a Scandinavian country and zero otherwise
<i>D_Deaths</i>	A dummy variable taking a value of one if the respondent is from a country with an above-median number of COVID-19 deaths and zero otherwise
<i>D_Shadow</i>	A dummy variable taking a value of one if the respondent's country has an above-median size of the shadow economy (as a percentage of GDP) and zero otherwise
<i>D_Stringency</i>	A dummy variable taking a value of one if the respondent resides in a country with an above-median value of the COVID stringency index and zero otherwise
<i>D_Developed</i>	A dummy variable taking a value of one if the respondent inhabits a country with an above-median value of GDP per capita in international dollars in 2020 and zero otherwise
<i>D_PD</i>	A dummy variable taking a value of one if the respondent is from a country with an above-median value of Hofstede power distance indicator and zero otherwise
<i>D_UA</i>	A dummy variable taking a value of one if the respondent is from a country with an above-median value of Hofstede uncertainty avoidance index and zero otherwise
<i>D_Terminals</i>	A dummy variable taking a value of one if the respondent's country has an above-median number of EFT-POS terminals per thousand people and zero otherwise

epidemic. As is shown in Appendix B, respondents in all of the Scandinavian countries in our sample (Denmark, Finland, Norway, Sweden) showed below-average tendency to change their habits in response to infection risk. Similarly, many of them failed to act out their fears through switching from cash to payment instruments offering a lower risk of virus transmission. Scandinavia had already been characterized by a very high level of electronic payments prior to the COVID outbreak (Armeliuss, Claussen, and Reslow 2022; Engert, Fung, and Segendorf 2020), which limited the scope of further abandonment of physical currency for transactional purposes. Secondly, the impact of changes in habits in the physical space is lessened for countries with high values of the COVID stringency index. In such countries, changes in behavior may have been primarily driven by the regulations rather than the free will of respondents. Switch to cashless payments, which is entirely voluntary in

Table I.2. Modeling the Switch to Cashless Payments during the Pandemic (including interaction terms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Gender</i>	0.1616** (0.0779)	0.1627** (0.0779)	0.1536** (0.0778)	0.1642** (0.0779)	0.1585** (0.0779)	0.1636** (0.0779)	0.1563** (0.0779)	0.1558** (0.0778)
<i>Location Size</i>	0.0189 (0.0255)	0.0194 (0.0255)	0.0185 (0.0255)	0.0200 (0.0254)	0.0202 (0.0255)	0.0193 (0.0254)	0.0185 (0.0255)	0.0190 (0.0256)
<i>Age</i>	0.0063** (0.0026)	0.0063** (0.0026)	0.0063** (0.0026)	0.0062** (0.0026)	0.0062** (0.0026)	0.0061** (0.0026)	0.0063** (0.0026)	0.0065** (0.0026)
<i>Cards & Mobile</i>	0.7320** (0.1337)	0.7251** (0.1332)	0.7337** (0.1338)	0.7256** (0.1332)	0.7240** (0.1337)	0.7295** (0.1340)	0.7311** (0.1338)	0.7360** (0.1338)
<i>Anonymity</i>	-0.1082*** (0.0349)	-0.1066** (0.0348)	-0.1084*** (0.0348)	-0.1061** (0.0348)	-0.1084*** (0.0349)	-0.1068*** (0.0348)	-0.1100*** (0.0349)	-0.1060*** (0.0348)
<i>Convenience of Cashless Payments</i>	-0.0214 (0.0560)	-0.0218 (0.0560)	-0.0236 (0.0560)	-0.0198 (0.0559)	-0.0246 (0.0561)	-0.0197 (0.0559)	-0.0236 (0.0560)	-0.0244 (0.0560)
<i>Safety of Cashless Payments</i>	0.1133* (0.0605)	0.1174* (0.0605)	0.1152* (0.0605)	0.1190** (0.0607)	0.1135* (0.0605)	0.1205** (0.0609)	0.1115* (0.0604)	0.1155* (0.0607)
<i>Access to Cashless Payments Technologies</i>	-0.0348 (0.0553)	-0.0374 (0.0551)	-0.0362 (0.0551)	-0.0358 (0.0551)	-0.0364 (0.0552)	-0.0377 (0.0551)	-0.0302 (0.0553)	-0.0356 (0.0551)
<i>Ease of Use of Cashless Technologies</i>	0.1581** (0.0618)	0.1587** (0.0618)	0.1560** (0.0618)	0.1572** (0.0618)	0.1616*** (0.0618)	0.1573** (0.0618)	0.1602*** (0.0618)	0.1529** (0.0617)
<i>Control over Finance with Cashless Payments</i>	-0.0247 (0.0544)	-0.0219 (0.0544)	-0.0213 (0.0544)	-0.0208 (0.0544)	-0.0244 (0.0545)	-0.0204 (0.0544)	-0.0254 (0.0546)	-0.0201 (0.0545)
<i>Literacy in Using Mobile Apps</i>	0.3641*** (0.0473)	0.3624*** (0.0473)	0.3635*** (0.0472)	0.3639*** (0.0474)	0.3637*** (0.0472)	0.3632*** (0.0474)	0.3638*** (0.0472)	0.3641*** (0.0471)
<i>Experience in Using Computer Payments</i>	0.0219 (0.0373)	0.0195 (0.0372)	0.0206 (0.0373)	0.0206 (0.0373)	0.0231 (0.0373)	0.0224 (0.0372)	0.0201 (0.0371)	0.0213 (0.0371)
<i>Experience in Using Mobile Payments</i>	0.0185 (0.0458)	0.0198 (0.0459)	0.0164 (0.0458)	0.0196 (0.0460)	0.0181 (0.0460)	0.0192 (0.0460)	0.0189 (0.0457)	0.0207 (0.0459)
<i>COVID Deaths</i>	0.0180** (0.0075)	0.0191** (0.0075)	0.0181** (0.0075)	0.0181** (0.0075)	0.0191** (0.0075)	0.0176** (0.0075)	0.0186** (0.0075)	0.0169** (0.0075)
<i>Shadow Economy</i>	-0.0202*** (0.0059)	-0.0201*** (0.0058)	-0.0195*** (0.0060)	-0.0202*** (0.0058)	-0.0210*** (0.0059)	-0.0217*** (0.0060)	-0.0201*** (0.0060)	-0.0203*** (0.0059)

(continued)

Table I.2. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0011 (0.0026)	0.0012 (0.0026)	0.0012 (0.0026)	0.0014 (0.0025)	0.0012 (0.0026)	0.0019 (0.0026)	0.0013 (0.0026)	0.0022 (0.0025)
<i>Net Fear of Cash</i>	0.2598*** (0.0430)	0.2740*** (0.0466)	0.2389*** (0.0500)	0.2252*** (0.0521)	0.2179*** (0.0437)	0.2343*** (0.0567)	0.1837** (0.0759)	0.2554*** (0.0428)
<i>Change in Habits Related to Physical Contact</i>	0.4489*** (0.0441)	0.4283*** (0.0498)	0.4889*** (0.0531)	0.5459*** (0.0580)	0.4407*** (0.0454)	0.3894*** (0.0600)	0.5221*** (0.0922)	0.4971*** (0.0464)
<i>Change in Online Habits</i>	0.0977** (0.0414)	0.0798* (0.0457)	0.0745 (0.0474)	0.1323** (0.0549)	0.1022** (0.0424)	0.0389* (0.0337)	0.1471* (0.0814)	0.0952** (0.0423)
<i>Net Fear of Cash × D_Scand</i>	-0.2067** (0.0857)							
<i>Change in Habits Related to Physical Contact × D_Scand</i>	0.0604 (0.1037)							
<i>Change in Online Habits × D_Scand</i>	-0.0017 (0.0849)							
<i>Net Fear of Cash × D_Deaths</i>		-0.1187 (0.0892)						
<i>Change in Habits Related to Physical Contact × D_Deaths</i>		0.0777 (0.0903)						
<i>Change in Online Habits × D_Deaths</i>		0.0626 (0.0816)						
<i>Net Fear of Cash × D_Shadow</i>			0.0230 (0.0780)					
<i>Change in Habits Related to Physical Contact × D_Shadow</i>			-0.1201 (0.0826)					
<i>Change in Online Habits × D_Shadow</i>			0.0953 (0.0758)					
<i>Net Fear of Cash × D_Stringency</i>				0.0343 (0.0749)				
<i>Change in Habits Related to Physical Contact × D_Stringency</i>				-0.1584** (0.0805)				
<i>Change in Online Habits × D_Stringency</i>				-0.0609 (0.0735)				
<i>Net Fear of Cash × D_Developed</i>					0.2248*** (0.0726)			
<i>Change in Habits Related to Physical Contact × D_Developed</i>					0.1565* (0.0840)			
<i>Change in Online Habits × D_Developed</i>					-0.0293 (0.0740)			
<i>Net Fear of Cash × D_PD</i>						0.0247 (0.0762)		

(continued)

Table I.2. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Change in Habits Related to Physical Contact</i> × <i>D_PD</i>						0.1432* (0.0816)		
<i>Change in Online Habits</i> × <i>D_PD</i>						0.1311* (0.0739)		
<i>Net Fear of Cash</i> × <i>D-UA</i>							0.0838 (0.0884)	
<i>Change in Habits Related to Physical Contact</i> × <i>D-UA</i>							-0.0903 (0.1028)	
<i>Change in Online Habits</i> × <i>D-UA</i>							-0.0616 (0.0904)	
<i>Net Fear of Cash</i> × <i>D-Terminals</i>								-0.0869 (0.1200)
<i>Change in Habits Related to Physical Contact</i> × <i>D-Terminals</i>								-0.2770*** (0.1075)
<i>Change in Online Habits</i> × <i>D-Terminals</i>								0.0239 (0.1062)
Constant	-0.7413** (0.2911)	-0.7634*** (0.2902)	-0.7542*** (0.2917)	-0.7552*** (0.2903)	-0.7347** (0.2908)	-0.7368** (0.2917)	-0.7486** (0.2917)	-0.7822*** (0.2911)
Observations	5,504	5,504	5,504	5,504	5,504	5,504	5,504	5,504
chi2	445.9	431.3	434.2	446.5	514.9	448.2	434.8	430.6
p	0	0	0	0	0	0	0	0
r2-p	0.117	0.117	0.117	0.118	0.118	0.118	0.117	0.118

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2 and in Table I.1. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

nature, did not seem to keep up with the regulation-induced behavioral shifts. Thirdly, the variable *Net Fear of Cash* exerted a more prominent impact on decision to abandon cash in countries with high GDP per capita. This is unsurprising since the volume of transactions is expected to be higher for respondents from affluent nations. As more cash transactions are made, the risks are swiftly compounding, and the desire to drift away from cash becomes stronger. This, in turn, explains the statistical significance of the interaction variable. Lastly, the impact of *Change in Habits Related to Physical Contact* on the decision to switch to digital payments is weaker in countries with a large number of EFT-POS terminals per capita.

Table I.3 presents models which include interactive terms and in which the intention to increase the frequency of cashless payments after the pandemic is over acts as a dependent variable.

Two of the interactions in Table I.3 appear to be significant at the 5 percent level. Firstly, the impact of changes in habits in the physical sphere on the declared future intention is stronger in societies with a high power distance. Power distance, as the degree to which hierarchical order is accepted within society, could affect trust in institutions and, consequently, in cashless technologies. If a person feels no resistance towards power distance and is prepared to change their physical habits, transition towards cashless payments will loom large on their agenda due to the relatively high trust in financial institutions. Such rationalization is consistent with the observed positive coefficient on the interaction term. Secondly, the societal uncertainty avoidance also appears to magnify the impact of *Change in Habits Related to Physical Contact* on the future intention to transact more cashless. This means that respondents who were willing to change their physical behavior in response to the dangers posed by COVID and resided in uncertainty-averse nations were particularly eager to abandon cash for transactional purposes.

Table I.3. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (including interaction terms)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Gender</i>	0.1768** (0.0843)	0.1821** (0.0842)	0.1772** (0.0843)	0.1820** (0.0842)	0.1765** (0.0844)	0.1856** (0.0842)	0.1809** (0.0844)	0.1729** (0.0842)
<i>Location Size</i>	0.0133 (0.0272)	0.0131 (0.0272)	0.0134 (0.0272)	0.0138 (0.0272)	0.0133 (0.0273)	0.0131 (0.0272)	0.0136 (0.0272)	0.0129 (0.0273)
<i>Age</i>	0.0046 (0.0029)	0.0047 (0.0029)	0.0048 (0.0029)	0.0046 (0.0029)	0.0047 (0.0029)	0.0045 (0.0029)	0.0044 (0.0029)	0.0047 (0.0029)
<i>Cards & Mobile</i>	0.7325*** (0.1440)	0.7322*** (0.1440)	0.7336*** (0.1440)	0.7257*** (0.1436)	0.7298*** (0.1439)	0.7340*** (0.1440)	0.7398*** (0.1443)	0.7378*** (0.1443)
<i>Anonymity</i>	-0.1124*** (0.0391)	-0.1094*** (0.0390)	-0.1127*** (0.0391)	-0.1107*** (0.0391)	-0.1132*** (0.0391)	-0.1085*** (0.0391)	-0.1108*** (0.0391)	-0.1113*** (0.0389)
<i>Convenience of Cashless Payments</i>	0.0290 (0.0620)	0.0297 (0.0622)	0.0272 (0.0620)	0.0311 (0.0621)	0.0269 (0.0621)	0.0335 (0.0621)	0.0346 (0.0622)	0.0260 (0.0620)
<i>Safety of Cashless Payments</i>	0.2709*** (0.0700)	0.2758*** (0.0701)	0.2725*** (0.0702)	0.2743*** (0.0699)	0.2716*** (0.0701)	0.2747*** (0.0701)	0.2715*** (0.0695)	0.2730*** (0.0701)
<i>Access to Cashless Payments Technologies</i>	-0.0788 (0.0652)	-0.0777 (0.0650)	-0.0778 (0.0651)	-0.0757 (0.0650)	-0.0795 (0.0652)	-0.0768 (0.0650)	-0.0776 (0.0653)	-0.0785 (0.0651)
<i>Ease of Use of Cashless Technologies</i>	0.2135*** (0.0718)	0.2118*** (0.0719)	0.2122*** (0.0718)	0.2127*** (0.0717)	0.2144*** (0.0718)	0.2121*** (0.0717)	0.2166*** (0.0718)	0.2085*** (0.0716)
<i>Control over Finance with Cashless Payments</i>	0.0711 (0.0609)	0.0768 (0.0608)	0.0712 (0.0608)	0.0740 (0.0607)	0.0715 (0.0607)	0.0761 (0.0607)	0.0682 (0.0606)	0.0739 (0.0608)
<i>Literacy in Using Mobile Apps</i>	0.1197** (0.0515)	0.1197** (0.0516)	0.1194** (0.0514)	0.1210** (0.0516)	0.1196** (0.0514)	0.1209** (0.0516)	0.1166** (0.0513)	0.1202** (0.0515)
<i>Experience in Using Computer Payments</i>	0.0469 (0.0427)	0.0440 (0.0427)	0.0463 (0.0426)	0.0448 (0.0426)	0.0471 (0.0426)	0.0456 (0.0424)	0.0505 (0.0427)	0.0467 (0.0426)
<i>Experience in Using Mobile Payments</i>	0.0345 (0.0485)	0.0326 (0.0488)	0.0364 (0.0485)	0.0336 (0.0488)	0.0349 (0.0486)	0.0340 (0.0486)	0.0393 (0.0485)	0.0359 (0.0487)
<i>COVID Deaths</i>	0.0185** (0.0078)	0.0177** (0.0081)	0.0183** (0.0078)	0.0177** (0.0078)	0.0190** (0.0078)	0.0163** (0.0080)	0.0184** (0.0078)	0.0171** (0.0078)
<i>Shadow Economy</i>	-0.0022 (0.0063)	-0.0019 (0.0063)	-0.0014 (0.0066)	-0.0018 (0.0063)	-0.0026 (0.0063)	-0.0039 (0.0065)	-0.0026 (0.0063)	-0.0018 (0.0063)
<i>Number of EFT-POS Terminals per Thousand People</i>	-0.0036 (0.0028)	-0.0034 (0.0028)	-0.0035 (0.0028)	-0.0034 (0.0028)	-0.0036 (0.0028)	-0.0027 (0.0028)	-0.0036 (0.0028)	-0.0020 (0.0028)
<i>Net Fear of Cash</i>	0.4024*** (0.0509)	0.4252*** (0.0552)	0.3958*** (0.0597)	0.3473*** (0.0591)	0.3791*** (0.0523)	0.4081*** (0.0691)	0.4475*** (0.0894)	0.4111*** (0.0505)

(continued)

Table I.3. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Change in Habits Related to Physical Contact</i>	0.9850*** (0.0579)	0.9207*** (0.0639)	1.0027*** (0.0697)	1.0920*** (0.0722)	0.9892*** (0.0600)	0.8713*** (0.0771)	0.7927*** (0.1125)	1.0271*** (0.0609)
<i>Change in Online Habits</i>	0.1147** (0.0475)	0.1100** (0.0519)	0.1205** (0.0548)	0.0797 (0.0618)	0.1145** (0.0489)	0.1309** (0.0619)	0.2220** (0.0917)	0.1049** (0.0485)
<i>Net Fear of Cash × D_Scam</i>	-0.0902 (0.0926)							
<i>Change in Habits Related to Physical Contact × D_Scam</i>	-0.0089 (0.1250)							
<i>Change in Online Habits × D_Scam</i>	-0.0875 (0.0965)							
<i>Net Fear of Cash × D_Deaths</i>		-0.1036 (0.1037)						
<i>Change in Habits Related to Physical Contact × D_Deaths</i>		0.2193* (0.1164)						
<i>Change in Online Habits × D_Deaths</i>		-0.0008 (0.0929)						
<i>Net Fear of Cash × D_Shadow</i>			-0.0005 (0.0918)					
<i>Change in Habits Related to Physical Contact × D_Shadow</i>			-0.0622 (0.1067)					
<i>Change in Online Habits × D_Shadow</i>			-0.0404 (0.0861)					
<i>Net Fear of Cash × D_Stringency</i>				0.0876 (0.0880)				
<i>Change in Habits Related to Physical Contact × D_Stringency</i>				-0.1827* (0.1007)				
<i>Change in Online Habits × D_Stringency</i>				0.0501 (0.0831)				
<i>Net Fear of Cash × D_Developed</i>					0.1346* (0.0815)			
<i>Change in Habits Related to Physical Contact × D_Developed</i>					-0.0330 (0.0996)			
<i>Change in Online Habits × D_Developed</i>					-0.0442 (0.0823)			
<i>Net Fear of Cash × D_PD</i>						-0.0228 (0.0898)		

(continued)

Table I.3. (Continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Change in Habits Related to Physical Contact</i> × <i>D_PD</i>						0.2526** (0.1036)		
<i>Change in Online Habits</i> × <i>D_PD</i>						-0.0494 (0.0834)		
<i>Net Fear of Cash</i> × <i>D-UA</i>							-0.0760 (0.1038)	
<i>Change in Habits Related to Physical Contact</i> × <i>D-UA</i>							0.2548** (0.1278)	
<i>Change in Online Habits</i> × <i>D-UA</i>							-0.1479 (0.1022)	
<i>Net Fear of Cash</i> × <i>D-Terminals</i>								-0.1018 (0.1404)
<i>Change in Habits Related to Physical Contact</i> × <i>D-Terminals</i>								-0.2499* (0.1340)
<i>Change in Online Habits</i> × <i>D-Terminals</i>								0.0289 (0.1226)
Constant	-1.2376*** (0.3119)	-1.2580*** (0.3112)	-1.2612*** (0.3142)	-1.2472*** (0.3113)	-1.2340*** (0.3115)	-1.2292*** (0.3137)	-1.2389*** (0.3132)	-1.2904*** (0.3123)
Observations	5,504	5,504	5,504	5,504	5,504	5,504	5,504	5,504
chi2	597.5	563.9	567.9	608.9	663.7	616.1	561.1	546.2
p	0	0	0	0	0	0	0	0
r2-p	0.223	0.224	0.223	0.224	0.223	0.225	0.225	0.224

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2 and in Table I.1. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Appendix J

Table J.1. Modeling the Switch to Cashless Payments during the Pandemic (probit estimates)

	(1)	(2)	(3)
<i>Gender</i>	0.1054** (0.0465)	0.0906* (0.0470)	0.0952** (0.0472)
<i>Location Size</i>	0.0164 (0.0151)	0.0091 (0.0153)	0.0111 (0.0154)
<i>Age</i>	0.0029* (0.0015)	0.0039** (0.0016)	0.0038** (0.0016)
<i>Cards & Mobile</i>	0.4067*** (0.0782)	0.4529*** (0.0789)	0.4450*** (0.0788)
<i>Anonymity</i>	-0.0346* (0.0205)	-0.0760*** (0.0210)	-0.0671*** (0.0211)
<i>Convenience of Cashless Payments</i>	0.0043 (0.0328)	-0.0169 (0.0339)	-0.0140 (0.0339)
<i>Safety of Cashless Payments</i>	0.0719** (0.0363)	0.0748** (0.0364)	0.0678* (0.0366)
<i>Access to Cashless Payments Technologies</i>	0.0138 (0.0326)	-0.0234 (0.0332)	-0.0201 (0.0334)
<i>Ease of Use of Cashless Technologies</i>	0.0933** (0.0367)	0.1008*** (0.0373)	0.0953** (0.0374)
<i>Control over Finance with Cashless Payments</i>	0.0078 (0.0324)	-0.0117 (0.0328)	-0.0134 (0.0331)
<i>Literacy in Using Mobile Apps</i>	0.2323*** (0.0285)	0.2248*** (0.0286)	0.2233*** (0.0287)
<i>Experience in Using Computer Payments</i>	0.0397* (0.0219)	0.0110 (0.0220)	0.0140 (0.0222)
<i>Experience in Using Mobile Payments</i>	0.0253 (0.0271)	0.0082 (0.0280)	0.0101 (0.0278)
<i>COVID Deaths</i>	0.0150*** (0.0044)	0.0108** (0.0045)	0.0112** (0.0045)
<i>Shadow Economy</i>	-0.0081** (0.0035)	-0.0117*** (0.0035)	-0.0122*** (0.0035)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0019 (0.0015)	0.0001 (0.0015)	0.0006 (0.0016)
<i>Net Fear of Cash</i>	0.1718*** (0.0233)		0.1495*** (0.0237)
<i>Change in Habits Related to Physical Contact</i>		0.2877*** (0.0249)	0.2749*** (0.0250)
<i>Change in Online Habits</i>		0.0599** (0.0239)	0.0601** (0.0240)
Constant	-0.6550*** (0.1705)	-0.3842** (0.1742)	-0.4484** (0.1748)
Observations	5,504	5,504	5,504
chi2	374.5	433.7	479.1
p-value	0	0	0
McFadden's Pseudo R-squared	0.0887	0.109	0.117

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Switch* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

Table J.2. Modeling the Intention to Use More Cashless Payments after the Pandemic Is Over (probit estimates)

	(1)	(2)	(3)
<i>Gender</i>	0.1136** (0.0475)	0.0895* (0.0495)	0.0966* (0.0501)
<i>Location Size</i>	0.0164 (0.0153)	0.0040 (0.0161)	0.0072 (0.0162)
<i>Age</i>	0.0015 (0.0016)	0.0030* (0.0017)	0.0025 (0.0017)
<i>Cards & Mobile</i>	0.3277*** (0.0831)	0.4430*** (0.0845)	0.4256*** (0.0847)
<i>Anonymity</i>	0.0059 (0.0210)	-0.0789*** (0.0227)	-0.0680*** (0.0230)
<i>Convenience of Cashless Payments</i>	0.0405 (0.0336)	0.0145 (0.0360)	0.0151 (0.0364)
<i>Safety of Cashless Payments</i>	0.1437*** (0.0375)	0.1588*** (0.0405)	0.1520*** (0.0407)
<i>Access to Cashless Payments Technologies</i>	0.0306 (0.0339)	-0.0457 (0.0373)	-0.0384 (0.0379)
<i>Ease of Use of Cashless Technologies</i>	0.1110*** (0.0382)	0.1365*** (0.0413)	0.1277*** (0.0418)
<i>Control over Finance with Cashless Payments</i>	0.0729** (0.0329)	0.0353 (0.0354)	0.0341 (0.0360)
<i>Literacy in Using Mobile Apps</i>	0.0958*** (0.0286)	0.0797*** (0.0302)	0.0757*** (0.0305)
<i>Experience in Using Computer Payments</i>	0.0737*** (0.0233)	0.0225 (0.0240)	0.0290 (0.0245)
<i>Experience in Using Mobile Payments</i>	0.0444 (0.0278)	0.0193 (0.0287)	0.0224 (0.0288)
<i>COVID Deaths</i>	0.0173*** (0.0045)	0.0097** (0.0046)	0.0107** (0.0046)
<i>Shadow Economy</i>	0.0065* (0.0036)	-0.0010 (0.0037)	-0.0012 (0.0037)
<i>Number of EFT-POS Terminals per Thousand People</i>	0.0004 (0.0015)	-0.0029* (0.0016)	-0.0021 (0.0016)
<i>Net Fear of Cash</i>	0.2617*** (0.0253)		0.2273*** (0.0270)
<i>Change in Habits Related to Physical Contact</i>		0.5853*** (0.0304)	0.5690*** (0.0307)
<i>Change in Online Habits</i>		0.0605** (0.0258)	0.0614** (0.0262)
Constant	-1.0988*** (0.1734)	-0.6081*** (0.1804)	-0.6986*** (0.1830)
Observations	5,504	5,504	5,504
chi2	436.8	587.3	609.2
p-value	0	0	0
McFadden's Pseudo R-squared	0.122	0.203	0.221

Note: This table reports regression coefficients of weighted logit regressions in which *Cashless Intention* acts as a dependent variable. Variable definitions can be found in Table 2. Robust standard errors are shown in parentheses. ***, **, and * denote statistical significance at 1 percent, 5 percent, and 10 percent, respectively.

References

- Abrams, B. L. 1972. "Dirty Money." *JAMA: The Journal of the American Medical Association* 219 (9): 1202–03.
- Ajzen, I., and M. Fishbein. 1980. *Understanding Attitudes and Predicting Social Behavior*. Prentice-Hall.
- Angelakis, E., E. I. Azhar, F. Bibi, M. Yasir, A. K. Al-Ghamdi, A. M. Ashshi, A. G. Elshemi, and D. Raoult. 2014. "Paper Money and Coins as Potential Vectors of Transmissible Disease." *Future Microbiology* 9 (2): 249–61.
- Arango, C., K. P. Huynh, and L. Sabetti. 2015. "Consumer Payment Choice: Merchant Card Acceptance Versus Pricing Incentives." *Journal of Banking and Finance* 55 (June): 130–41.
- Arango-Arango, C. A., Y. Bouhdaoui, D. Bounie, M. Eschelbach, and L. Hernandez. 2018. "Cash Remains Top-of-Wallet! International Evidence From Payment Diaries." *Economic Modelling* 69 (January): 38–48.
- Ardizzi, G., A. Nobili, and G. Rocco. 2020. "A Game Changer in Payment Habits: Evidence From Daily Data During a Pandemic." Occasional Paper No. 591, Banca d'Italia.
- Armeliuss, H., C. A. Claussen, and A. Reslow. 2022. "Withering Cash: Is Sweden Ahead of the Curve or Just Special?" *International Journal of Central Banking* 18 (4): 91–123.
- Auer, R., G. Cornelli, and J. Frost. 2020. "COVID-19, Cash, and the Future of Payments." BIS Bulletin No. 3, Bank for International Settlements.
- Bagnall, J., D. Bounie, K. P. Huynh, A. Kosse, T. Schmidt, S. Schuh, and H. Stix. 2016. "Consumer Cash Usage: A Cross-Country Comparison with Payment Diary Survey Data." *International Journal of Central Banking* 12 (4): 1–59.
- Bank for International Settlements. 2022. "BIS Payments and Financial Market Infrastructures Statistics." Available at <https://stats.bis.org/statx/toc/CPMI.html>.
- Basavarajappa, K. G., P. N. S. Rao, and K. Suresh. 2005. "Study of Bacterial, Fungal, and Parasitic Contamination of Currency Notes in Circulation." *Indian Journal of Pathology and Microbiology* 48 (2): 278–79.

- Beijnen, C., and W. Bolt. 2009. "Size Matters: Economies of Scale in European Payments Processing." *Journal of Banking and Finance* 33 (2): 203–10.
- Bick, A., A. Blandin, and K. Mertens. 2023. "Work from Home Before and After the COVID-19 Outbreak." *American Economic Journal: Macroeconomics* 15 (4): 1–39.
- Boeschoten, W. C., and M. M. G. Fase. 1989. "The Way We Pay with Money." *Journal of Business and Economic Statistics* 7 (3): 319–26.
- Bolt, W., and D. B. Humphrey. 2007. "Payment Network Scale Economies, SEPA, and Cash Replacement." *Review of Network Economics* 6 (4): 453–73.
- Bolt, W., N. Jonker, and C. van Renselaar. 2010. "Incentives at the Counter: An Empirical Analysis of Surcharging Card Payments and Payment Behaviour in the Netherlands." *Journal of Banking and Finance* 34 (8): 1738–44.
- Bounie, D., Y. Camara, and J. W. Galbraith. 2023. "Consumer Mobility and Expenditure During the COVID-19 Containments: Evidence from French Transaction Data." *European Economic Review* 151 (January): Article 104326.
- Bounie, D., A. François, and L. Van Hove. 2017. "Consumer Payment Preferences, Network Externalities, and Merchant Card Acceptance: An Empirical Investigation." *Review of Industrial Organization* 51 (3): 257–90.
- Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe. 2020. "COVID-19 and Remote Work: An Early Look at US Data." NBER Working Paper No. 27344.
- Carden, L., and W. Wood. 2018. "Habit Formation and Change." *Current Opinion in Behavioral Sciences* 20 (3): 117–22.
- Carvalho, V. M., J. R. García, S. Hansen, Á. Ortiz, T. Rodrigo, S. R. Mora, and P. Ruiz. 2021. "Tracking the COVID-19 Crisis With High-Resolution Transaction Data." *Royal Society Open Science* 8 (8): Article 2102182.
- Caswell, E., M. H. Smith, D. Learmonth, and G. Pearce. 2020. "Cash in the Time of COVID." Quarterly Bulletin No. Q4, Bank of England.
- Cevik, S. 2020. "Dirty Money: Does the Risk of Infectious Disease Lower Demand for Cash?" *International Finance* 23 (3): 460–71.

- Chen, H., W. Engert, K. P. Huynh, G. Nicholls, M. W. Nicholson, and J. Zhu. 2020. "Cash and COVID-19: The Impact of the Pandemic on the Demand for and Use of Cash." Discussion Paper No. 2020–6, Bank of Canada.
- Chernova, Y. 2019. "Fintech Startups Face Tough Exit Options." *The Wall Street Journal*, December 30.
- Chin, A. W. H., J. T. S. Chu, M. R. A. Perera, K. P. Y. Hui, H.-L. Yen, M. C. W. Chan, M. Peiris, and L. L. M. Poon. 2020. "Stability of SARS-CoV-2 in Different Environmental Conditions." *The Lancet Microbe* 1 (1): e10.
- Dahlhaus, T., and A. Welte. 2021. "Payment Habits During COVID-19: Evidence from High-Frequency Transaction Data." Staff Working Paper No. 2021–43, Bank of Canada.
- Danchev, S., G. Gatopoulos, and N. Vettas. 2020. "Penetration of Digital Payments in Greece After Capital Controls: Determinants and Impact on VAT Revenues." *CESifo Economic Studies* 66 (3): 198–220.
- Davis, F. D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology." *MIS Quarterly* 13 (3): 319–40.
- DeYoung, R., and T. Rice. 2004. "How Do Banks Make Money? The Fallacies of Fee Income." *Economic Perspectives* 28 (4): 34–51.
- De Nederlandsche Bank. 2020. "Shift of Cash to Debit Card Continues." DNBulletin, April 20.
- Engert, W., and B. S. C. Fung. 2019. "Cashless Bank Branches in Canada." Staff Analytical Note No. 2019–29, Bank of Canada.
- Engert, W., B. S. C. Fung, and B. Segendorf. 2020. "A Tale of Two Countries: Cash Demand in Canada and Sweden." In *International Cash Conference 2019—Cash in the Age of Payment Diversity*, 365–425. Deutsche Bundesbank.
- Esselink, H., and L. Hernández. 2017. "The Use of Cash by Households in the Euro Area." Occasional Paper No. 201, European Central Bank.
- European Central Bank. 2020. "Study on the Payment Attitudes of Consumers in the Euro Area (SPACE)."
- . 2022. "ECB Payments Statistics." Available at <https://data.ecb.europa.eu/publications/payments-statistics/3075435>.
- Eurostat. 2020. "Digital Economy and Society Statistics — Households and Individuals." Available at <https://ec.europa>

- .eu/eurostat/statistics-explained/index.php/Digital_economy_and_society_statistics_-_households_and_individuals (accessed February 28, 2021).
- Fishbein, M., and I. Ajzen. 1975. *Belief, Attitude, Intention, and Behavior: An Introduction to Theory and Research*. Addison-Wesley.
- Foster, K., C. Greene, and J. Stavins. 2020. *The 2019 Survey of Consumer Payment Choice: Summary Results*. Research Data Report No. 20–3, Federal Reserve Bank of Atlanta.
- Fu, J., and M. Mishra. 2022. “The Global Impact of COVID-19 on Fintech Adoption.” *Journal of Financial Intermediation* 50 (April): Article 100945.
- Galbraith, J. W., and G. Tkacz. 2013. “Analyzing Economic Effects of September 11 and Other Extreme Events Using Debit and Payments System Data.” *Canadian Public Policy* 39 (1): 119–34.
- Gedik, H., T. A. Voss, and A. Voss. 2013. “Money and Transmission of Bacteria.” *Antimicrobial Resistance and Infection Control* 2 (22).
- Ghosh, P., B. Vallee, and Y. Zeng. 2021. “FinTech Lending and Cashless Payments.” Paper presented at the Paris December Finance Meeting organized by EUROFIDAI (European Financial Data Institute) and ESSEC Business School, December 16.
- Gomber, P., R. J. Kauffman, C. Parker, and B. W. Weber. 2018. “On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services.” *Journal of Management Information Systems* 35 (1): 220–65.
- Goodhart, C. A., and J. Ashworth. 2020. “Coronavirus Panic Fuels a Surge in Cash Demand.” CEPR Discussion Paper No. 14910.
- Gordon, J. P. F. 1990. “Evading Taxes by Selling for Cash.” *Oxford Economic Papers* 42 (1): 244–55.
- Greene, C., and J. Stavins. 2020. “The 2019 Diary of Consumer Payment Choice.” Research Data Report No. 20–4, Federal Reserve Bank of Atlanta.
- Grewenig, E., P. Lergetporer, L. Simon, K. Werner, and L. Woessmann. 2023. “Can Internet Surveys Represent the Entire Population? A Practitioners’ Analysis.” *European Journal of Political Economy* 78 (June): Article 102382.

- Hair, J. F., W. C. Black, B. J. Babin, and R. E. Anderson. 2013. *Multivariate Data Analysis: Pearson New International Edition*, 7th ed. Pearson Education.
- Harbourt, D. E., A. D. Haddow, A. E. Piper, H. Bloomfield, B. J. Kearney, D. Fetterer, K. Gibson, and T. Minogue. 2020. “Modeling the Stability of Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) on Skin, Currency, and Clothing.” *PLOS Neglected Tropical Diseases* 14 (11): e0008831.
- Haubrich, J. G., and T. Young. 2019. “Trends in the Noninterest Income of Banks.” Economic Commentary No. 2019-14, Federal Reserve Bank of Cleveland.
- Hondroyannis, G., and D. Papaoikonomou. 2017. “The Effect of Card Payments on VAT Revenue: New Evidence From Greece.” *Economics Letters* 157 (August): 17–20.
- . 2020. “The Effect of Card Payments on VAT Revenue in the Euro Area: Evidence from a Panel VECM.” *Journal of Economic Studies* 47 (6): 1281–1306.
- Hosmer, D. W., S. Lemeshow, and R. X. Sturdivant. 2013. *Applied Logistic Regression*, 3rd ed. John Wiley & Sons.
- Humphrey, D. B., M. Willeson, G. Bergendahl, and T. Lindblom. 2006. “Benefits from a Changing Payment Technology in European Banking.” *Journal of Banking and Finance* 30 (6): 1631–52.
- Immordino, G., and F. F. Russo. 2018. “Cashless Payments and Tax Evasion.” *European Journal of Political Economy* 55 (December): 36–43.
- Jonker, N., C. van der Crujisen, M. Bijlsma, and W. Bolt. 2022. “Pandemic Payment Patterns.” *Journal of Banking and Finance* 143 (October): Article 106593.
- Kelly, J. 2020. “The Virus Has Crushed the Challenger Bank Dream.” *Financial Times*, November 8.
- Kelmanson, B., K. Kirabaeva, L. Medina, B. Mircheva, and J. Weiss. 2019. “Explaining the Shadow Economy in Europe: Size, Causes and Policy Options.” Working Paper No. 19/278, International Monetary Fund.
- Khiaonarong, T. 2003. “Payment Systems Efficiency, Policy Approaches, and the Role of the Central Bank.” Discussion Paper No. 1/2003, Bank of Finland.

- Kim, L., R. Kumar, and S. O'Brien. 2020. "Consumer Payments & the COVID-19 Pandemic: A Supplement to the 2020 Findings from the Diary of Consumer Payment Choice." FedNotes, Federal Reserve Bank of San Francisco.
- King, R., and A. Shen. 2020. "Will Cash Survive COVID-19?" *Central Banking*, March 20.
- Kodoth, V. 2020. "Party's Over: A Maturing FinTech Industry Faces Its Reckoning." *Forbes*, December 15.
- Kotkowski, R. 2023. "National Culture and the Demand for Physical Money During the First Year of the COVID-19 Pandemic." *Finance Research Letters* 51 (January): Article 103483.
- Kotkowski, R., M. Dulnicz, and K. Maciejewski. 2022. *Payment Habits in Poland in 2020*. Narodowy Bank Polski.
- Koulayev, S., M. Rysman, S. Schuh, and J. Stavins. 2016. "Explaining Adoption and Use of Payment Instruments by US Consumers." *RAND Journal of Economics* 47 (2): 293–325.
- KPMG. 2020. *Pulse of Fintech H1 2020*. KPMG.
- Kraenzlin, S., C. Meyer, and T. Nellen. 2020. "COVID-19 and Regional Shifts in Swiss Retail Payments." *Swiss Journal of Economics and Statistics* 156 (14).
- Lally, P., C. H. M. van Jaarsveld, H. W. W. Potts, and J. Wardle. 2010. "How Are Habits Formed: Modelling Habit Formation in the Real World." *European Journal of Social Psychology* 40 (6): 998–1009.
- Li, X., H. Feng, S. Zhao, and D. A. Carter. 2021. "The Effect of Revenue Diversification on Bank Profitability and Risk During the COVID-19 Pandemic." *Finance Research Letters* 43 (November): Article 101957.
- Madzharova, B. 2020. "Traceable Payments and VAT Design: Effects on VAT Performance." *CESifo Economic Studies* 66 (3): 221–47.
- Maritz, J. M., S. A. Sullivan, R. J. Prill, E. Aksoy, P. Scheid, and J. M. Carlton. 2017. "Filthy Lucre: A Metagenomic Pilot Study of Microbes Found on Circulating Currency in New York City." *PLOS ONE* 12 (4): e0175527.
- Mastercard. 2020. "Mastercard Enables Contactless Limit Raise Across 29 Countries; And Champions Permanent Increase." Press Release, March 25.

- Mathieu, E., H. Ritchie, L. Rodés-Guirao, C. Appel, C. Giattino, J. Hasell, B. Macdonald, et al. 2020. "Coronavirus Pandemic (COVID-19)." Published online at OurWorldInData.org.
- McKinsey & Company. 2020a. *Detour: An Altered Path for European Fintechs*. McKinsey & Company.
- . 2020b. *How US Customers' Attitudes to Fintech Are Shifting During the Pandemic*. McKinsey & Company.
- . 2022. *The 2022 McKinsey Global Payments Report*. McKinsey & Company.
- Mínguez, J. G., A. Urtasun, and M. P. G. de Mirasierra. 2020. "Consumption in Spain During the State of Alert: An Analysis Based on Payment Card Spending." *Economic Bulletin* No. 3/2020, Banco de España.
- Moro, A., D. Maresch, M. Fink, A. Ferrando, and C. Piga. 2020. "Spillover Effects of Government Initiatives Fostering Entrepreneurship on the Access to Bank Credit for Entrepreneurial Firms in Europe." *Journal of Corporate Finance* 62 (June): Article 101603.
- Nabity-Grover, T., C. M. K. Cheung, and J. B. Thatcher. 2020. "Inside Out and Outside In: How the COVID-19 Pandemic Affects Self-Disclosure on Social Media." *International Journal of Information Management* 55 (December): Article 102188.
- Norges Bank. 2020. "Retail Payment Services 2019." Norges Bank Paper No. 1, Norges Bank.
- O'Driscoll, M., G. R. D. Santos, L. Wang, D. A. T. Cummings, A. S. Azman, J. Paireau, A. Fontanet, et al. 2021. "Age-Specific Mortality and Immunity Patterns of SARS-CoV-2." *Nature* 590 (7844): 140–45.
- Ostlund, L. E. 1974. "Perceived Innovation Attributes as Predictors of Innovativeness." *Journal of Consumer Research* 1 (2): 23–29.
- Pal, R., and S. K. Bhadada. 2020. "Cash, Currency and COVID-19." *Postgraduate Medical Journal* 96 (1137): 427–28.
- Png, I. P. L., and C. H. Y. Tan. 2020. "Privacy, Trust in Banks, and Use of Cash." *Macroeconomic Review* (Monetary Authority of Singapore) XIX (April): 109–16.
- Polasik, M., A. Huterska, R. Iftikhar, and Š. Mikula. 2020. "The Impact of Payment Services Directive 2 on the PayTech Sector Development in Europe." *Journal of Economic Behavior and Organization* 178 (October): 385–401.

- Pope, T. W., P. T. Ender, W. K. Woelk, M. A. Koroscil, and T. M. Koroscil. 2002. "Bacterial Contamination of Paper Currency." *Southern Medical Journal* 95 (12): 1408–10.
- Radecki, L. J. 1999. "Banks' Payments-Driven Revenues." *Economic Policy Review* 5 (2): 53–70.
- Rambure, D., and A. Nacamuli. 2008. *Payment Systems. From the Salt Mines to the Board Room*. Palgrave Macmillan.
- Restoy, F. 2020. "Central Banks and Financial Stability: A Reflection After the COVID-19 Outbreak." Occasional Paper No. 16, Financial Stability Institute.
- Riddell, S., S. Goldie, A. Hill, D. Eagles, and T. W. Drew. 2020. "The Effect of Temperature on Persistence of SARS-CoV-2 on Common Surfaces." *Virology Journal* 17: Article 145.
- Saroy, R., S. Awasthy, N. K. Singh, S. M. Adki, and S. Dhal. 2022. "The Impact of COVID-19 on Digital Payment Habits of Indian Households." *Bulletin of Monetary Economics and Banking* 25 (Special Issue): 19–42.
- Schneider, F. 2019. "Restricting or Abolishing Cash: An Effective Instrument for Eliminating the Shadow Economy, Corruption and Terrorism?" In *Cash on Trial, Mk II: Economics, Technology and Institutions*, ed. U. Birchler, E. Gnan, C.-C. Hedrich, and J. Ulbrich, 53–70. SUERF — The European Money and Finance Forum.
- Schuh, S., and J. Stavins. 2016. "How Do Speed and Security Influence Consumers' Payment Behavior?" *Contemporary Economic Policy* 34 (4): 595–613.
- Shiffrin, R. M., and W. Schneider. 1977. "Controlled and Automatic Human Information Processing: II. Perceptual Learning, Automatic Attending and a General Theory." *Psychological Review* 84 (2): 127–90.
- Simon, J., K. Smith, and T. West. 2010. "Price Incentives and Consumer Payment Behaviour." *Journal of Banking and Finance* 34 (8): 1759–72.
- Snellman, J. S., J. M. Vesala, and D. B. Humphrey. 2001. "Substitution of Noncash Payment Instruments for Cash in Europe." *Journal of Financial Services Research* 19 (2): 131–45.
- Stavins, J. 2001. "Effect of Consumer Characteristics on the Use of Payment Instruments." *New England Economic Review* (Federal Reserve Bank of Boston) 3: 19–31.

- Stavins, J., and O. Shy. 2015. "Merchant Steering of Consumer Payment Choice: Evidence from a 2012 Diary Survey." *Journal of Behavioral and Experimental Economics* 55 (13): 1–9.
- Tagoe, D., S. Baidoo, I. Dadzie, and D. Ahator. 2009. "A Study of Bacterial Contamination of Ghanaian Currency Notes in Circulation." *Internet Journal of Microbiology* 8 (2).
- Tamele, B., A. Zamora-Pérez, C. Litardi, J. Howes, E. Steinmann, and D. Todt. 2021. "Catch Me (If You Can): Assessing the Risk of Sars-Cov-2 Transmission via Euro Cash." Occasional Paper No. 259, European Central Bank.
- Thakor, A. V. 2020. "Fintech and Banking: What Do We Know?" *Journal of Financial Intermediation* 41 (January): Article 100833.
- Uneke, C. J., and O. Ogbu. 2007. "Potential for Parasite and Bacteria Transmission by Paper Currency in Nigeria." *Journal of Environmental Health* 69 (9): 54–62.
- van der Cruijssen, C., and F. van der Horst. 2019. "Cash or Card? Unravelling the Role of Socio-Psychological Factors." *De Economist* 167 (2): 145–75.
- van Doremalen, N., T. Bushmaker, D. H. Morris, M. G. Holbrook, A. Gamble, B. N. Williamson, A. Tamin, et al. 2020. "Aerosol and Surface Stability of SARS-CoV-2 as Compared with SARS-CoV-1." *New England Journal of Medicine* 382 (16): 1564–67.
- Vriesekoop, F., J. Chen, J. Oldaker, F. Besnard, R. Smith, W. Leversha, C. Smith-Arnold, et al. 2016. "Dirty Money: A Matter of Bacterial Survival, Adherence, and Toxicity." *Microorganisms* 4 (4): Article 42.
- Wang, Z. 2016. "Price Cap Regulation in a Two-Sided Market: Intended and Unintended Consequences." *International Journal of Industrial Organization* 45 (March): 28–37.
- Watanabe, T., and Y. Omori. 2020. "Online Consumption During the COVID-19 Crisis: Evidence from Japan." Working Paper No. F-487, Center for Advanced Research in Finance.
- Webb, A., R. McQuaid, and S. Rand. 2020. "Employment in the Informal Economy: Implications of the COVID-19 Pandemic." *International Journal of Sociology and Social Policy* 40 (9–10): 1005–19.

- White, H. 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity." *Econometrica* 48 (4): 817–38.
- World Health Organization. 2020. "Coronavirus Disease (COVID-19) Pandemic." Available at <https://www.who.int/emergencies/diseases/novel-coronavirus-2019> (accessed February 28, 2021).
- Yeung, K. 2020. "China Central Bank Branch to Destroy Banknotes from Coronavirus-Hit Sectors." *South China Morning Post*, February 16.
- Zhang, Y., G. Zhang, L. Liu, T. D. Renzis, and H. Schmiedel. 2019. "Retail Payments and the Real Economy." *Journal of Financial Stability* 44 (October): Article 100690.